Price Elasticity with Non-linear Contract: Evidence from the RAND Health Insurance Experiment

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Abstract

Due to the random assignment of coinsurance rates, the RAND Health Insurance Experiment (HIE) is widely regarded as the gold standard for estimating the elasticity of demand for medical care. A key limitation of the experiment is that a large portion of the sample reached their Maximum Dollar Expenditure (MDE), reducing their coinsurance rates to zero. This potentially led to a compression in spending across experimental groups, which would understate the elasticity of demand. To address this issue, I propose an alternative two-part model that separately analyzes households with below- and above-MDE medical spending. Using maximum likelihood estimation, I find that the price elasticity of demand for medical care is -0.250, approximately 20% larger in magnitude than the estimate of -0.209 obtained by replicating the widely cited findings of Manning et al. (1987). I also show that households are more responsive to changes in outpatient coinsurance rates compared to inpatient, mental health, and dental services at both the extensive and intensive margins.

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I. Introduction

As the RAND Health Insurance Experiment (HIE) randomly assigned coinsurance rates to a sample of non-elderly individuals, estimates from this experiment are considered by many to be the gold standard estimate for the elasticity of demand for medical care. For example, the Congressional Budget Office in its simulations of the likely impact of the Affordable Care Act uses estimates from the HIE as the basis of their simulations. Using a four-part model, Manning et al. (1987) estimated the arc price elasticity of demand for medical care to be about -0.2, which remains the most well-known estimate for the elasticity of demand for medical care in the literature.[0] One issue Manning et al. (1987) had to address in their analysis of the RAND HIE was the highly non-linear nature of the health insurance in the experiment, which results from the Maximum Dollar Expenditure (MDE) feature that caps individuals' out-of-pocket (OOP) spending for covered medical care before they face a zero coinsurance rate. This feature could greatly alter individuals' medical spending behavior. Consider, for instance, the two extreme insurance policies in the experiment: one with a 0% coinsurance rate and the other with a 95% coinsurance rate. For the latter policy, once the family's medical spending reaches the MDE, the coinsurance rate would drop to zero, which means that for high-spending families, the disparity between spending in the low and high coinsurance groups would decline, reducing demand elasticity estimates across groups. Therefore, ignoring these features may lead to estimation results that are biased toward zero. The solution the authors proposed to tackle this potential underestimation issue was to restrict the sample to fee-for-service (FFS) households whose OOP spending is more than $400 from the MDE, assuming that nominal and real prices for medical care are equal to

0 The four-part model consists of the following components: The first equation is a Probit model that determines whether a household used any medical service during the contract year. The second equation, also a Probit model, determines whether a household had any inpatient stay conditional on receiving some medical service during the contract year. The third equation is an Ordinary Least Squares (OLS) model that estimates the logarithm of annual total medical expenditure for households that received exclusively outpatient services during the contract year. Similarly, the fourth equation is an OLS model that estimates the logarithm of annual total medical expenditure for households that received exclusively inpatient services during the contract year.

each other for those households. This simple fix led to a significant portion of households being excluded from the analysis.

This paper proposes an alternative two-part model for measuring the price elasticity of medical care without excluding any FFS households from the analysis. Cost-sharing affects demand for medical care in two ways. At the extensive margin, it may affect the probability that a household demands any medical service during a contract year. At the intensive margin, it may affect the amount of medical service a household demands conditional on receiving any medical service. Therefore, I estimate a two-part model using maximum likelihood estimation where the first part is a Probit model that estimates the price elasticity of demand for medical care at the extensive margin. The second part of the model is a piecewise regression that estimates the price elasticity of demand for medical care at the extensive margin by modeling the data-generating process (DGP) of household-level health care spending using two different equations based on whether the assigned MDE has been reached or not.

In the analysis, I replicate the findings of Manning et al. (1987) using a two-part equivalent of their four-part model. In subsequent sections of this paper, this model will be referred to as the "Manning model". Specifically, instead of examining the expenses of households that use only outpatient services and households that use any inpatient service separately, I do not distinguish these two groups in the two-part version of the model to make the estimate comparable to that from my model. The estimate obtained from this model is -0.2088, which is very similar to the published estimate. Next, using the alternative model, I show that the price elasticity of demand for medical care is -0.2497. The findings suggest that the basic fix proposed by Manning et al. (1987), which aims to address the issue of a large fraction of families reaching the MDE with their OOP spending, underestimates the elasticity of demand for medical care by approximately 16%.

There is a vast literature on the impact of cost-sharing on the demand for medical care. Besides the famous RAND estimate of -0.2 (Manning et al., 1987; Keeler and Rolph, 1988), researchers have also studied how cost-sharing affects demand for medical care using the Oregon Health Insurance Experiment (OHIE), which is more recent compared to the RAND HIE. The OHIE began in 2008 when the state of Oregon expanded access to Medicaid for low-income adults based on lottery drawings. Individuals who won the lottery would be able to enroll in Medicaid, so the opportunity to enroll in Medicaid was randomized. Using the OHIE data, Taubman et al. (2014) found that individuals who won the lottery on average increased their emergency room visits by about 40%. Another study by Baicker et al. (2017) found that Oregon's Medicaid expansion in 2008 led to an 11.6-percentage-point increase in the share of people having a prescription medication. They also show that the number of prescription medications per person increased by 0.46.

Several other studies have examined the effect of the Stanford Group Health Plan reform in 1968 on the demand for medical care (Newhouse and Phelps, 1976; Scitovsky and Snyder, 1972; Scitovsky and McCall, 1977). The reform introduced a 25 percent coinsurance rate for medical services that were previously free of charge. By studying the demand for medical care among the same individuals before and after the reform, Phelps and Newhouse (1972) showed that the arc elasticity of demand for physician visits was -0.14, with female enrollees being more sensitive to the price change. The other two studies found similar effects of cost-sharing.

Other studies that lack exogenous variation in coinsurance rates produced a wide variation in elasticities. Rosett and Huang (1973) found a price elasticity of -0.35 at a 20% coinsurance rate and -1.5 at an 80% coinsurance rate by analyzing the cross-sectional data from the 1960 Survey of Consumer Expenditure. Feldstein (1971) found a price elasticity of demand for hospital services of -1.12 using a dynamic twelve-equation model. Newhouse and Phelps (1976) estimated a price elasticity of -0.24 for hospital services and -0.42 for physician services using a generalized Grossman investment model. Although these studies used a wide variety of data sources and models to estimate the price elasticity of demand, the effect of MDE on the estimation was overlooked due to data limitations and the difficulty of modeling these nonlinear contracts. The non-experimental nature of these studies raises concerns about insurance endogeneity and makes it difficult to distinguish between time trends and the actual cost-sharing effect. Compared to previous work, the approach and data used in this paper provide a price elasticity estimate that is free from potential endogeneity and unobserved time trend issues and more relevant to real-world health policy-making.

II. Data

The data source for my analysis is the RAND HIE. This experiment was conducted between 1974 and 1981 in six different sites across the United States. More than 7,700 individuals under age 62 from 2,750 households were recruited. Participating households were assigned to either one of the FFS plans or the HMO plan. Due to the fundamental differences between the types of physician networks these two types of plans offer, my analysis focuses solely on households randomly assigned to one of the FFS plans. Column 1 of Table 1 shows the number of individuals and households assigned to each plan. These FFS plans feature a wide range of coinsurance rates and MDE, so there is enough variation in the data for estimating the elasticity.

There are six basic categories of FFS plans, each with varying degrees of cost-sharing: free care, 25% coinsurance, 50% coinsurance, 95% coinsurance, 95% coinsurance for outpatient care and free hospital care, and a sixth category with 50% coinsurance for dental and outpatient mental health services and 25% coinsurance for all other services. Each category, except the fourth, consists of three plans that differ by the MDE, which is set at the minimum of 5%, 10%, or 15% of family income, or $1,000. Since the MDE applies to the entire household, the unit of analysis is the household-contract-year, although most health care usage determinants are measured at the individual level. Individuals assigned to the plans in the fourth category face a $150 individual out-of-pocket maximum. However, if the household's aggregate OOP medical spending reaches $450, then each household member is eligible for free care afterward no matter whether the individual dollar limit has been reached or not. Therefore, we need to consider two cases when determining the proper unit of analysis for plans in this category: family size less than or equal to three and family size greater than three. In the former case, the family-level MDE can never be reached without each household member reaching the individual-level MDE, so the family-level MDE does not affect individuals' health care consumption behavior. Therefore, the proper unit of analysis is person-contract-year. For the latter case, both the individual-level and family-level MDE could affect individuals' decision-making when consuming health care, so the true MDE and the proper unit of analysis cannot be determined. Thus, households with more than three members assigned to plans in the fourth category are excluded from the analysis.

In the data, health care services are grouped into a single episode based on a common complaint, diagnosis, or treatment. In addition to this information, the experiment also collected detailed demographic information. Since the unit of analysis is the household-contract-year, I constructed family-level controls from individual-level demographic data such as age and sex to measure the number of male and female household members by age group. Other family-level controls include family income and whether at least one household member was insured before the experiment.

A key variable in the analysis is the MDE. Figure 1 illustrates the percentage of households whose OOP medical spending reached the MDE across the six plan categories. In total, more than half of the households reached their assigned MDE. However, this variable cannot be directly used in the model as it is not on the same scale as the outcome of interest. To tackle this incomparability issue, I constructed a variable called Implied MDE (*IMDE*). For households whose OOP medical spending reached the MDE, *IMDE* measures the total medical spending when the dollar limit is reached. Otherwise, *IMDE* measures what the value would have been if the dollar limit had been reached at some point during a given contract year. For plans with a single coinsurance rate, *IMDE* is inferred from the coinsurance rate and MDE. For plans with varying coinsurance rates across different medical services, if the dollar limit is reached, *IMDE* is calculated from the total cost of each treatment episode, episode type, and the MDE at the start and end of the episode. If the dollar limit is not reached, *IMDE* is derived from historical distributions of household medical spending on each service type.

III. Empirical Framework

To examine the elasticity of demand for medical care in the presence of MDE, my analysis proceeds in three steps. First, I estimate the Manning model to replicate the findings of Manning et al. (1987). Second, I estimate an alternative two-part model that explicitly accounts for the DGP of medical spending. Third, I compare the price elasticity of demand estimates for medical care from both models to assess whether the Manning model's estimates are biased either toward or away from zero.

III.A. The Manning Model

I estimate the Manning model using maximum likelihood estimation. The first part models the change in the likelihood of a household receiving any medical care during a given contract year as a response to changes in coinsurance rates:

$$\begin{gathered} Y_{1it}^{*} = \theta_0 + \beta_1 C_{Ii} + \beta_2 C_{Oi} + \beta_3 C_{MDi} + \boldsymbol{X_{it}\alpha_1} + \nu_{it} \\ Y_{1it} = 1 \text{ if } Y_{1it}^{*} \geq 0 \\ Y_{1it} = 0 \text{ if } Y_{1it}^{*} < 0 \end{gathered} \tag{1}$$

The binary indicator variable Y_{1it} indicates whether household i's total medical expenditure is positive in policy year t. The vector $\boldsymbol{X}$ measures time-variant and time-invariant covariates. The independent variables C_I, C_O, and C_M represent the coinsurance rates for inpatient care, outpatient care, and mental health and dental care, respectively. The error term in the latent variable representation of the Probit model, ν_{it}, follows a standard normal distribution. The second part of the model examines the change in the logarithm of total medical spending in response to changes in coinsurance rates, conditional on the household having positive medical expenditure:

$$Y_{2it} = \phi_0 + \phi_1 C_{Ii} + \phi_2 C_{Oi} + \phi_3 C_{Mi} + \boldsymbol{X_{it}\alpha_2} + \epsilon_{it} \tag{2}$$

The outcome of interest Y_2 is the logarithm of total medical spending. The vector $\boldsymbol{X}$ is a set of time-variant and time-invariant household-level covariates. The independent variables C_I, C_O, and C_M represent the coinsurance rates for inpatient care, outpatient care, and mental health and dental care, respectively. The error term, ϵ_{it} is normally distributed where $\epsilon_{it} \sim N(0, \eta^2)$. Unlike the four-part model that separates outpatient-only individuals from those who received inpatient services, the two-part model does not distinguish between these groups.

To estimate this model, I use the likelihood function derived by Duan et al. (1983). Additionally, since households were enrolled in the experiment for three or five years, they could appear in the sample multiple times. Therefore, standard errors are clustered at the household level to account for correlations in the error terms across contract years for the same household. Not accounting for these correlations could lead to high Type I error rates. Following Manning et al. (1987), the sample is restricted to households whose OOP spending is more than \$400 from the MDE in the second part of the model. The underlying assumption is that those households would treat the probability of reaching the MDE as zero, whereas households whose OOP spending is less than \$400 from the MDE would discount the nominal price of medical care by a non-zero probability of reaching the MDE, which means that including the latter group of households would underestimate the price elasticity of demand for medical care.

III.B. Two-Part Model: An Alternative Approach

III.B.1 Model Setup

To examine the price elasticity of demand for medical care without having to restrict the sample to a subset of all FFS households, I estimate an alternative two-part model with cross-equation restrictions using maximum likelihood estimation that allows all FFS households to be included in the analysis. The first part models whether there is any positive spending, which is identical to the first part of the Manning model. The second part of the model is a piecewise regression that distinguishes between households based on whether their positive annual total medical expenditure exceeds the *IMDE.*:

$$Y_{2it} = \begin{cases} \gamma_0 + \lambda_1 C_{Ii} + \lambda_2 C_{Oi} + \lambda_3 C_{Mi} + \boldsymbol{X_{it}\alpha_2} + \tau_{it} & \text{if } Y_{2it} \leq \mathit{ln(IMDE_{it})} \\ \gamma_1 + \boldsymbol{X_{it}\alpha_2} + \tau_{it} & \text{otherwise} \end{cases} \tag{3}$$

The outcome variable, Y_{2it}, measures the logarithm of household i's total medical expenditure in policy year t conditional on the household having positive total medical expenditure. The independent variables C_I, C_O, and C_M represent the coinsurance rates for inpatient care, outpatient care, and mental health and dental care, respectively. The vector $\boldsymbol{X}$ is a set of time-variant and time-invariant household-level covariates.

In this model, the coefficients on the control variables are assumed to be equal across the two equations in the piecewise regression, as represented by Equation 3. These cross-equation restrictions ensure that the effects of household characteristics are homogeneous across both regimes, which is likely reflective of real-world conditions. To test whether these restrictions are statistically justified, I compared the restricted model against an unrestricted alternative that allows the coefficients on control variables to vary across regimes using a likelihood ratio test. The resulting p-value of 0.052 indicates rejection of the null hypothesis of equal coefficients at the 10% significance level. Nevertheless, I use the restricted model in my analysis because the unrestricted model's regime-specific differences lack a coherent behavioral foundation in our context of non-linear health insurance contracts. For example, while household characteristics such as size or composition should affect baseline medical need, which is a level effect, there is no theoretical reason why they would systematically modify the response to reaching the MDE, which is a marginal price effect.

Another assumption I make in the model is that $\tau \sim N(0, \sigma_2^2)$. Note that in the second part of the model, the error terms are set to be the same across the two regimes. This is because, in reality, households' annual total medical spending is likely drawn from a single underlying distribution rather than multiple distributions conditional on positive spending. I also assume that the error terms ϵ and τ are independent of each other following the assumption made by Manning et al. (1987). In addition, I assume that Y_2 is normally distributed given X where $Y_2 \sim N(\gamma_0 + \boldsymbol{C\lambda} + \boldsymbol{X\alpha_2}, \sigma_2^2)$ when $Y_2 \leq \mathit{ln(IMDE)}$ and $Y_2 \sim N(\gamma_1 + \boldsymbol{X\alpha_2}, \sigma_2^2)$ otherwise. Figure 2 shows that the logarithmic transformation of total family medical expenditure follows a roughly normal distribution, which justifies the use of a normal distribution when modeling the distribution of the logarithm of total medical expenditure. Moreover, since the data is panel data with multiple observations per household, I cluster the error terms at the household level to account for autocorrelation between observations of the same household across contract years.

In the Manning model, the sample is restricted to households whose OOP spending is more than \$400 from the MDE. The assumption is that for those households the probability of exceeding the MDE is zero, whereas for households whose OOP spending is between MDE−\$400 and MDE the probability of exceeding the MDE is positive. Under this assumption, nominal prices are equal to real prices for the former group. Therefore, restricting the sample to these households allows for a proper estimation of the price elasticity of demand for medical care using nominal prices. In my model, instead of imposing the same assumption that individuals are, to a large extent, forward-looking when consuming medical care, I assume that individuals behave myopically when consuming medical care. Under this assumption, households whose OOP spending is between MDE−\$400 and MDE are not distinguished from those whose OOP spending is below MDE−$400. This assumption helps simplify the model and avoid potential identification issues.

One caveat is that in real life, medical consumption behavior may not be completely myopic. There is a vast literature examining the degree of forward-lookingness in healthcare consumption with mixed findings. For example, Sacks et al. (2017) compared matched diabetic patients enrolled in Standard Medicare Part D plans or low-income subsidy (LIS) plans. They showed that seniors with diabetes adjust their medication adherence primarily in response to high immediate OOP costs rather than planning consumption based on the benefit's nonlinear structure throughout the year, which demonstrates myopic behavior. On the contrary, by leveraging variations in the timing of individuals' enrollment in health insurance contracts that reset on predetermined, fixed dates, Aron-Dine et al. (2015) demonstrated that individuals who enroll later in the year—facing the same spot price but a higher expected end-of-year price—exhibit lower initial medical utilization compared to those enrolling earlier. This finding suggests that consumers exhibit some degree of forward-looking behavior in their healthcare consumption. Given the mixed findings in the literature, assuming that individuals behave entirely myopically in healthcare consumption may oversimplify the complexities of real-world behavior, which may involve elements of forward-looking decision-making. Future research could extend the proposed model by incorporating varying degrees of forward-looking behavior to better capture the underlying patterns in healthcare consumption.

III.B.2 Likelihood Function

Let $\mu_{1it} = \theta_0 + \boldsymbol{C_{it}\beta} + \boldsymbol{X_{it}\alpha_1}$, $\mu_{2it} = \gamma_0 + \boldsymbol{C_{it}\lambda} + \boldsymbol{X_{it}\alpha_2}$, $\mu_{3it} = \gamma_1 + \boldsymbol{X_{it}\alpha_2}$, and $T_{it} =$ *ln(IMDE$_{it}$)*. Define D_{it} as an indicator that equals 1 if $Y_{2it} > T_{it}$ and 0 otherwise. The likelihood contribution of each observation can be computed as:

$$\begin{aligned} L_{it} &= Pr(Y_{1it}=0)^{1-Y_{1it}} \cdot [1-Pr(Y_{1it}=0)]^{Y_{1it}} \cdot f(Y_{2it} \mid T_{it})^{Y_{1it}} \\ &= Pr(Y_{1it}=0)^{1-Y_{1it}} \cdot [1-Pr(Y_{1it}=0)]^{Y_{1it}} \\ &\cdot [f(Y_{2it} \mid Y_{2it} \leq T_{it})^{1-D_{it}} \cdot f(Y_{2it} \mid Y_{2it} > T_{it})^{D_{it}}]^{Y_{1it}} \\ &= [1-\Phi(\mu_{1it})]^{1-Y_{1it}} \cdot \Phi(\mu_{1it})^{Y_{1it}} \\ &\cdot \left\{ \left[\frac{\frac{1}{\sigma_2}\phi\left(\frac{Y_{2it}-\mu_{2it}}{\sigma_2}\right)}{\Phi\left(\frac{T_{it}-\mu_{2it}}{\sigma_2}\right)} \right]^{1-D_{it}} \cdot \left[\frac{\frac{1}{\sigma_2}\phi\left(\frac{Y_{2it}-\mu_{3it}}{\sigma_2}\right)}{1-\Phi\left(\frac{T_{it}-\mu_{2it}}{\sigma_2}\right)} \right]^{D_{it}} \right\}^{Y_{1it}} \end{aligned} \tag{4}$$

The likelihood function for the two-part model can be computed as:

$$\mathcal{L} = \prod_{i=1}^{N} \prod_{t=1}^{T_i} L_{it} \tag{5}$$

N represents the number of clusters (households), and T_i denotes the number of time periods (contract years) for the i-th cluster. L_{it} represents the likelihood of the t-th observation in the i-th cluster. Maximizing the log-likelihood of $\mathcal{L}$ provides the maximum likelihood estimators for the effects of coinsurance rates across different types of medical services on medical spending at both the extensive and intensive margins, which can then be used to calculate the price elasticity of demand for medical care.

III.B.3 Adjustment for Within-Cluster Correlation

To estimate the standard errors of the parameters in Equation 1, I use the Generalized Estimating Equations (GEE) methodology developed by Liang and Zeger (1986) that provides consistent estimates in the presence of correlated data. For Equations 2 and 3, I apply cluster-robust variance estimators to account for clustering by modeling the covariance structure within each cluster:

$$\hat{V}(\hat{\beta}) = (X'X)^{-1}\left(\sum_{i=1}^{N} X_i'\hat{\Omega}_i X_i\right)(X'X)^{-1} \tag{6}$$

X is the design matrix for the entire sample. X_i is the design matrix for the *i-th* cluster. $\hat{\Omega}_i$ is the estimated variance-covariance matrix of the residuals for the *i-th* cluster, which accounts for heteroskedasticity and autocorrelation within that cluster. N is the number of clusters.

IV. Results

IV.A. Manning Model Estimation Results

Columns (1) and (2) of Table 2 present the estimation results for the first part of the Manning model. Column (1) shows the estimated coefficients for the three key independent variables — coinsurance rates for inpatient care, outpatient care, and mental health and dental care — as specified in Equation 1. The estimates for inpatient and outpatient coinsurance are -0.0020 and -0.0081, respectively. These estimated coefficients are statistically significant at the 5% and 10% levels, suggesting that higher inpatient and outpatient coinsurance rates, which correspond to an increase in the prices for these services, may reduce the likelihood of a household utilizing medical care. In contrast, the estimate for mental health and dental coinsurance is 0.0026 and statistically insignificant, suggesting that changes in the costs of mental health and dental care do not have a clear effect on the likelihood of medical care utilization. Column (2) shows the corresponding average marginal effects. For inpatient coinsurance, the average marginal effect is -0.0003, which implies that a 1-percentage-point increase in the inpatient coinsurance rate leads, on average, to a 0.03-percentage-point decrease in the probability of seeking medical care. Similarly, the average marginal effect of outpatient coinsurance is -0.0013, meaning that a 1-percentage-point increase in outpatient coinsurance results, on average, in a 0.13-percentage-point decrease in the likelihood of seeking medical care. Additionally, the average marginal effect of mental and dental coinsurance is 0.0004. However, this effect is statistically insignificant, suggesting that changes in mental health and dental coinsurance have a negligible impact on the likelihood of medical care utilization.

Column (3) of Table 2 presents the estimation results for the second part of the Manning model. The estimate for inpatient coinsurance is 0.0025. Although this estimate is positive, which is contrary to expectations, it is statistically insignificant, suggesting that changes in inpatient coinsurance rates have no discernible effect on the demand for inpatient care on the intensive margin. Similarly, the estimate for mental health and dental coinsurance is positive but statistically insignificant. This implies that changes in mental health and dental coinsurance rates do not have a discernible effect on the demand for these types of care. In contrast, the estimate for outpatient coinsurance is -0.0130, and it is statistically significant at the 1% level. This indicates that a 1 percentage point increase in outpatient coinsurance rates leads to a 1.3% increase in medical care utilization at the intensive margin.

IV.B. Alternative Model Estimation Results

Columns (1) and (2) of Table 2 present the estimation results for the first part of the alternative model, which are identical to those obtained from the first part of the Manning model. To understand why this is the case, note that Equation 4 can be factored into two multiplicative terms. Assume without loss of generality that there are N observations where the first n observations have positive medical expenditure and the remaining $N-n$ observations have zero medical expenditure. The first term

$$L_1 = \prod_{i=1}^{n} \Phi(\mu_{1i}) \cdot \prod_{i=n+1}^{N} [1 - \Phi(\mu_{1i})] \tag{7}$$

depends exclusively on the parameters in Equation 1. The second term

$$L_2 = \prod_{i=1}^{n} \left\{ \left[\frac{\frac{1}{\sigma_2} \phi \left(\frac{Y_{2i} - \mu_{2i}}{\sigma_2} \right)}{\Phi \left(\frac{T_i - \mu_{2i}}{\sigma_2} \right)} \right]^{1-D} \cdot \left[\frac{\frac{1}{\sigma_2} \phi \left(\frac{Y_{2i} - \mu_{3i}}{\sigma_2} \right)}{1 - \Phi \left(\frac{T_i - \mu_{2i}}{\sigma_2} \right)} \right]^{D} \right\} \tag{8}$$

depends exclusively on the parameters in Equation 3. When discussing the likelihood function of the two-part model that is used to overcome the nonspender issue, Duan et al. (1983) emphasized the separability of the likelihood function. Specifically, the likelihood function decomposes into two multiplicative terms: the first depends solely on the parameters of the first part of the model, and the second depends solely on the parameters of the second part, as shown earlier. Consequently, maximizing Equation 5 is equivalent to maximizing Equations 7 and 8 separately, yielding identical estimates. In this context, the separability of Equation 5 implies that both models produce identical estimates for the first part. Therefore, the focus is placed on comparing the estimates derived from the second part of the models.

Column (4) of Table 2 presents the estimation results for the second part of the alternative model. The estimate for inpatient coinsurance is 0.0031, which is only marginally significant. Based on the point estimate, this represents approximately a 24% increase compared to that from the Manning model. However, the Manning model's estimate falls within its confidence interval. The estimate for outpatient coinsurance is -0.0183, which is statistically significant at the 1% level and approximately 41% larger in magnitude compared to the estimate from the Manning model. In addition, the estimate for mental health and dental coinsurance is 0.0040, which is statistically insignificant. Based on the point estimate, this represents a 60% increase compared to that from the Manning model. However, the Manning model's estimate falls within its confidence interval. These results suggest that individuals' healthcare consumption is most responsive to changes in outpatient coinsurance, in line with the findings from the Manning model. However, the alternative model indicates a more elastic demand for outpatient care.

IV.C. Model Comparison

To compare the estimates of the elasticity from the two models, it is important to note that the price elasticity of demand for medical care is calculated by summing the elasticities at both the extensive and intensive margins. This approach captures households' full response to changes in the price of medical care. To calculate the elasticity at the extensive margin, which is crucial in understanding how price changes influence individuals' decisions to either seek or forgo medical care, I use the following formula:

$$
\begin{aligned}
\epsilon_e &= Extensive\ Margin\ Elasticity_{Inpatient} + Extensive\ Margin\ Elasticity_{Outpatient} \\
&\quad + Extensive\ Margin\ Elasticity_{Mental\&Dental} \\
&= p_I \frac{\partial Y_1}{\partial C_I} \frac{\bar{C}_I}{\bar{Y}_1} + p_O \frac{\partial Y_1}{\partial C_O} \frac{\bar{C}_O}{\bar{Y}_1} + p_M \frac{\partial Y_1}{\partial C_M} \frac{\bar{C}_M}{\bar{Y}_1}
\end{aligned} \tag{9}
$$

where p_I, p_O, and p_M represent the percentages of aggregate medical expenditure allocated to inpatient services, outpatient services, and mental health and dental services, respectively.[1] $\frac{\partial Y_1}{\partial C_I}$ represents the coefficient on inpatient coinsurance specified in Equation 1, which measures the change in the probability of a household utilizing medical care in response to a change in inpatient coinsurance rates. Similarly, $\frac{\partial Y_1}{\partial C_O}$ and $\frac{\partial Y_1}{\partial C_M}$ represent the Probit coefficients on outpatient coinsurance, as well as mental health and dental coinsurance. These coefficients measure the changes in the probability of utilizing medical care in response to changes in outpatient coinsurance rates and mental health and dental coinsurance rates, respectively. $\bar{C}_I$, $\bar{C}_O$, and $\bar{C}_M$ represent the weighted coinsurance rates for inpatient, outpatient, and mental health and dental services, respectively. They are calculated by weighting the coinsurance rates by the corresponding numbers of households assigned to those rates for each type of medical service. $\bar{Y}_1$ represents the proportion of households with positive total medical expenditure. Similarly, the price elasticity of demand for medical care at the

1 The aggregate medical expenditure refers to the total medical expenditure across all households in the sample.

intensive margin is calculated using the formula below:

$$
\begin{aligned}
\epsilon_i &= Intensive\ Margin\ Elasticity_{Inpatient} + Intensive\ Margin\ Elasticity_{Outpatient} \\
&\quad + Intensive\ Margin\ Elasticity_{Mental\&Dental} \\
&= p_I \frac{\partial Y_2}{\partial C_I} \bar{C}_I + p_O \frac{\partial Y_2}{\partial C_O} \bar{C}_O + p_M \frac{\partial Y_2}{\partial C_M} \bar{C}_M
\end{aligned} \tag{10}
$$

Similar to the partial derivatives in Equation 9, $\frac{\partial Y_2}{\partial C_I}$, $\frac{\partial Y_2}{\partial C_O}$ and $\frac{\partial Y_2}{\partial C_M}$ represent the piecewise regression coefficients on inpatient coinsurance, outpatient coinsurance, and mental health and dental coinsurance specified in Equations 2. These coefficients measure the percentage changes in medical care utilization at the intensive margin resulting from changes in inpatient, outpatient, and mental health and dental coinsurance rates, respectively.

Table 3 presents the estimated price elasticities of demand for medical care, calculated using Equations 9 and 10. The first row shows the elasticities at the extensive margin for both models, and the second row shows the elasticities at the intensive margin. Both models yield the same elasticity at the extensive margin, which is -0.1086. At the intensive margin, the estimated elasticity is -0.1002 in the Manning model and -0.1411 in the alternative model. Summing the elasticities at the extensive and intensive margins gives the overall price elasticity of demand for medical care. In the Manning model, the price elasticity is -0.2088, while in the alternative model, it is -0.2497. This suggests that the Manning model underestimates the price elasticity by approximately 16%.

V. Conclusion

In an effort to quantify the effect of cost-sharing on the demand for medical care, the Department of Health and Human Services funded the RAND Health Insurance Experiment (HIE) in 1971. Using data from the RAND HIE and accounting for the nonlinear insurance contracts due to the presence of an MDE, I estimate the price elasticity of demand for medical care to be -0.2497. Compared to the replicated elasticity estimate of -0.2088 derived from the Manning model, this suggests that the latter model understates the elasticity by approximately 16%.

There are several real-world implications of this higher price elasticity. First, the higher elasticity suggests that individuals may reduce their use of medical services more substantially when prices rise, which could occur through higher insurance premiums or increased copayments. This effect may be particularly pronounced for elective or non-essential services, as individuals are more likely to delay or forgo these services in response to rising costs compared to essential services. Second, from a policymaker's perspective, a more elastic demand for medical care indicates that changes in pricing policies, such as adjustments to Medicare cost-sharing, may have a larger impact on healthcare consumption than anticipated. This could raise concerns about access to essential medical services, especially among lower-income populations. Third, for health insurance providers, this suggests that pricing structures may need to be carefully balanced to avoid disproportionately deterring necessary care. If demand is more elastic, higher patient costs could reduce not only excessive use of services but also appropriate, medically necessary care, potentially leading to worse health outcomes over time. Lastly, a more elastic demand could result in greater fluctuations in the healthcare sector. If medical costs rise and people cut back on care, this could strain healthcare providers or lead to inefficiencies, such as delayed treatments that become more costly to address later. Conversely, lower prices might encourage greater utilization, potentially overwhelming healthcare resources or increasing overall costs for insurers.

The findings should be interpreted with caution due to several limitations. First, I use family-year as the unit of analysis, whereas using person-year would be more intuitive given that most major determinants of medical service utilization are measured at the individual level. However, since the MDE was assigned at the household level in most cases, the use of family-year is necessary. Another limitation is that the experiment only recruited individuals under the age of 62, so further research is needed to determine whether these findings can be generalized to individuals aged 62 and older. Overall, this study contributes to the understanding of the elasticity of demand for medical care, which has significant implications for policymakers and insurers as they design cost-sharing mechanisms that balance affordability, access to care, and efficient use of medical services.

VI. Figures and Tables

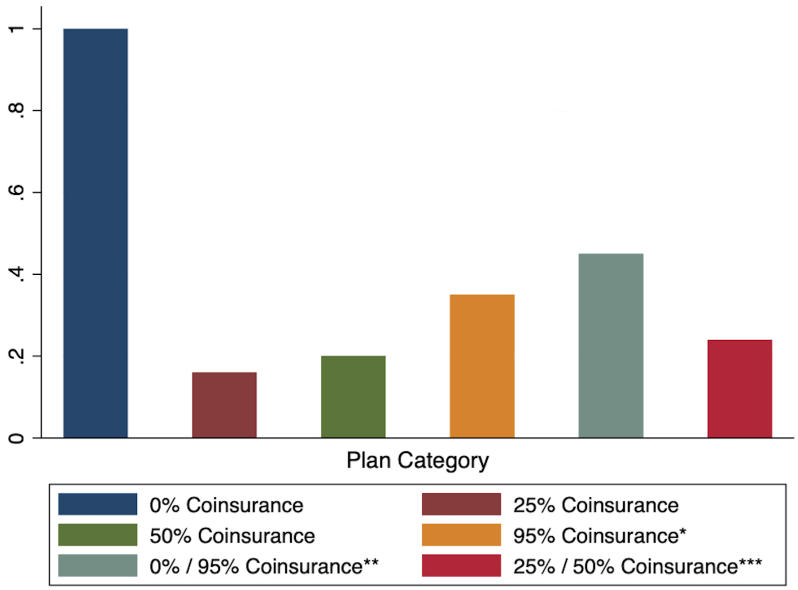

Figure 1: Percentage of Households with OOP Spending Reaching the MDE by Plan Category. * During the experiment's first year in Dayton, plans in this category had a 100% coinsurance rate. ** Plans in this category had a 95% outpatient coinsurance rate and a 0% inpatient coinsurance rate. For plans in this category, the y-axis represents the percentage of individuals, rather than households, whose OOP spending reached the MDE, as the MDE was assigned at the individual level rather than the household level. During the experiment's first year in Dayton, households assigned to these plans faced a 100% outpatient coinsurance rate. *** Plans in this category had a 50% coinsurance rate for dental and outpatient mental health services and a 25% coinsurance rate for all other medical services.

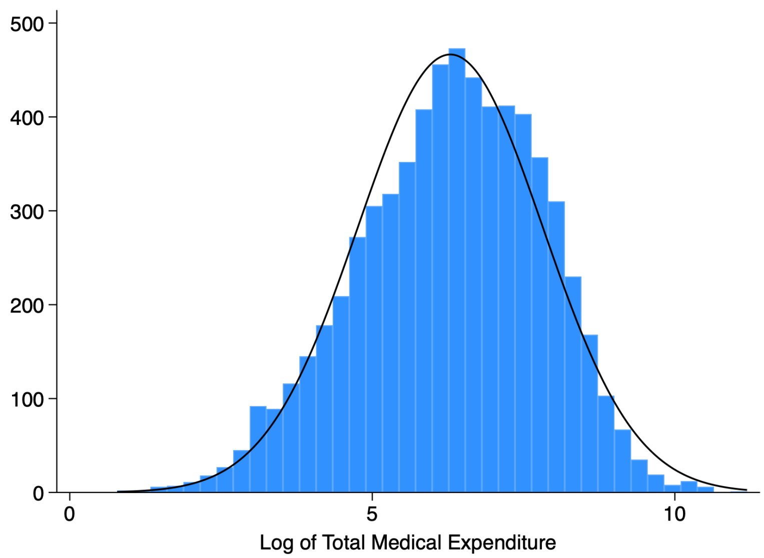

Figure 2: Logarithmic Transformation of Total Medical Expenditure. This figure presents the distribution of the logarithm of annual total medical expenditure for participating households, conditional on positive expenditure. As shown, the log-transformed annual total medical expenditure is approximately normally distributed.

Table 1: Summary Statistics by Health Insurance Plan

	Number of Households	Average Family Income	Coinsurance Rate	Maximum Dollar Expenditure
	(1)	(2)	(3)	(4)
Plan 1	35	11,885	Outpatient: 100% Inpatient: 0%	$450
Plans 2-4	116	12,285	100%	5%, 10%, or 15% of family income, or $1,000, whichever is less
Plans 5-7	268	11,170	25%	5%, 10%, or 15% of family income, or $750/$1,000, whichever is less
Plans 8-10	164	11,497	50%	5%, 10%, or 15% of family income, or $1,000, whichever is less
Plan 11	822	10,290	0%	$0
Plan 13	362	9,555	Outpatient: 95% Inpatient: 0%	$150 per individual, or $450 per family
Plans 14-16	356	9,237	95%	5%, 10%, or 15% of family income, or $1000, whichever is less
Plans 17-19	236	8,955	Dental and outpatient mental health: 50% Other services: 25%	5%, 10%, or 15% of family income, or $750/$1,000, whichever is less

Plan 1 features a 100% outpatient coinsurance rate and a 0% inpatient coinsurance rate. Plans 2-4 feature a 100% coinsurance rate. Plans 5-7 feature a 25% coinsurance rate. Plans 8-10 feature a 50% coinsurance rate. Plan 11 is a free plan. Plan 13 features a 95% outpatient coinsurance rate and a 0% inpatient coinsurance rate. Plans 14-16 feature a 95% coinsurance rate. Plans 17-19 feature a 50% coinsurance rate for dental and outpatient mental health services and a 25% coinsurance rate for all other medical services.

Table 2: Model Estimation Results: Impact of Coinsurance Rate Changes on Health Care Utilization

	Probit	Average Marginal Effect	OLS	Piecewise Regression
	(1)	(2)	(3)	(4)
Inpatient Coinsurance	-0.0020^{**}	-0.0003^{**}	0.0025	0.0031^{*}
	(0.0009)	(0.0001)	(0.0024)	(0.0017)
Outpatient Coinsurance	-0.0081^{*}	-0.0013^{*}	-0.0130^{***}	-0.0183^{***}
	(0.0049)	(0.0008)	(0.0028)	(0.0011)
Mental and Dental Coinsurance	0.0026	0.0004	0.0025	0.0040
	(0.0050)	(0.0008)	(0.0030)	(0.0029)

Column (1) presents the Probit estimates from the first part of both the Manning model and the alternative two-part model proposed in this paper. Column (2) reports the corresponding average marginal effects of a 1-percentage-point change in inpatient, outpatient, or mental and dental coinsurance rates on the likelihood of incurring positive medical expenditure. Column (3) reports the OLS estimates from the second part of the Manning model, assessing the impact of a 1-percentage-point change in the coinsurance rate on the amount of medical services demanded by households conditional on receiving any medical service. Similarly, Column (4) reports the estimates from the piecewise regression in the second part of the alternative model, evaluating the impact of a 1-percentage-point change in the coinsurance rate on the amount of medical services demanded by households conditional on receiving any medical service. Standard errors are shown in parentheses. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Table 3: Price Elasticity of Demand for Medical Care

	Probit + OLS (1)	Probit + Piecewise Regression (2)
Elasticity at the Extensive Margin	-0.1086^{***}	-0.1086^{***}
	(0.0134)	(0.0134)
Elasticity at the Intensive Margin	-0.1002^{***}	-0.1411^{***}
	(0.0128)	(0.0102)
Elasticity of Demand for Medical Care	-0.2088^{***}	-0.2497^{***}
	(0.0262)	(0.0236)

The final entry of Column (1) shows the estimate of the elasticity of demand for medical care using the Manning model. This estimate is the sum of the elasticity estimates at the extensive and intensive margins shown in the first two rows of Column (1). The final entry of Column (2) shows the estimate of the elasticity of demand for medical care using the alternative two-part model where the first part is a Probit regression and the second part is a piecewise regression. This estimate is the sum of the elasticity estimates at the extensive and intensive margins shown in the first two rows of Column (2). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

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