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## **Alternatives for Modeling Results from the RAND Health Insurance Experiment**

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## Summary

The RAND Health Insurance Experiment (HIE) was ongoing from the mid-1970s to the early 1980s. Two thousand nonelderly families from six urban and rural areas were randomly assigned health insurance plans with different levels of cost-sharing (that is, with various levels of deductibles, coinsurance, and out-of-pocket maximums). The results from this unprecedented health insurance experiment showed that people facing higher cost-sharing (that is, they had to pay a higher proportion of total health care costs out of their own pockets) had lower health care spending than those in plans with lower cost-sharing. No similar experiment has been performed since the HIE, so it remains the epochal analysis for understanding the link between health insurance cost-sharing and total health care spending. This report examines the methods used to apply the HIE results in health policy analyses.

The key variable used to try to explain health care spending in the HIE was the plans' coinsurance — that is, the *percentage* of total health care costs that the individual must pay. Understanding these results from the HIE was complicated by the fact that for each coinsurance rate, there were multiple plans, each with a different out-of-pocket maximum (although the maximum never exceeded \$1,000). For example, a person may have been enrolled in the “25% coinsurance plan,” but after that person had spent \$1,000 (or less) out of pocket, the plan effectively became a 0% coinsurance plan. Thus, the nominal coinsurance could not be used as the sole cost-sharing variable for explaining the impact of cost-sharing in the HIE plans.

The HIE results have been particularly useful for policy analysts estimating what effect changes in cost-sharing might have on health care spending — in public health insurance programs, for example. Microsimulation modeling is one tool used by health policy analysts to estimate the impact of cost-sharing changes. “Micro” refers to the fact that the modeling takes place on an individual level rather than an aggregate level, based on a database of individuals representative of a certain population (the U.S. population or a smaller subset, such as individuals enrolled in Medicaid). If one wanted to estimate the impact of an increase in coinsurance, for example, a microsimulation model would apply that increase to every person in the data along with a concomitant drop in total health care spending.

In most health insurance modeling, the HIE results remain the basis for adjusting total health care spending in response to cost-sharing changes. However, applying those results in a model is not always straightforward. One of two methods is typically used — elasticities, generally preferred by health economists, and induction, preferred by actuaries. Each has benefits and shortfalls, but little comparative analysis has been done. This report begins by generally describing and comparing elasticities and induction factors. The report then summarizes key findings from the HIE and discusses how elasticities and induction factors can be used to replicate those results. Because of the limitations of these methods in modeling, this report offers a third alternative that appears to better replicate the HIE results. This method, called the cubic formula, is simply a formula that produces HIE-reported spending levels from the experiment's four coinsurance levels.

## Contents

Theoretical Explanation of Cost-Sharing Methods	2
Elasticity of Demand	2
Health Insurance Applications	4
Induction Factors	5
Health insurance applications	7
Additional Comparisons	8
RAND Health Insurance Experiment	12
Selected Results	12
Calculating and Applying Cost-Sharing Methods Based on HIE Results	17
Arc Elasticities	17
Predicting Quantity with Point-elasticity and Arc-elasticity	
Formulas	18
Effect of Arc Elasticity's Lack of Path Neutrality	20
Induction Factors	22
Predicting Quantity with Induction Formulas	22
Cubic Formula	26
Estimating Free-Plan Spending	28
Predicting Spending From Estimated Free-Plan Spending	30
Pure Coinsurance Plan	30
Typical Plan Structure	31
Predicting Spending by Type of Care	35
Constant Induction Factors	36
Inpatient and Outpatient Care	36
Prescription Drugs	40
Conclusion	43

## List of Figures

Figure 1. Predicted Expenses Using Various Cost-Sharing Methods, from Example Case	9
Figure 2. Predicted Expenses Using Various Cost-Sharing Methods and Values, from Example Case Results at 15% Coinsurance	11
Figure 3. Effect of Nominal Coinsurance on Annual Per-Person Medical Expenses, in Dollars, from RAND Health Insurance Experiment	13
Figure 4. Effect of <i>Nominal</i> Coinsurance on Annual Per-Person Medical Expenses, as a Percentage of Free Plan Expenses	14
Figure 5. Effect of <i>Average</i> Coinsurance on Annual Per-Person Medical Expenses, as a Percentage of Free Plan Expenses	15
Figure 6. Analysis of Arc Elasticity's Lack of Path Neutrality in HIE Results: Predicting Quantity Varying By Beginning HIE Data Point	19
Figure 7. Illustration of Arc Elasticity's Lack of Path Neutrality: Predicting Quantity Varying Whether Beginning Data Point Was an Original HIE Point	21

Figure 8. Predicting Quantity Using Induction Factors and Original Data Points from HIE .....	23
Figure 9. Predicting Quantity of Inpatient Care, By Induction Factor and Beginning HIE Data Point .....	24
Figure 10. Comparison of Results of Constant Induction Factor from Free-Plan Spending with Induction Factors and Original Data Points from HIE .....	25
Figure 11. Predicting Quantity Using Cubic Formula, Compared to Ideal Arc Elasticities and Induction Factors, From Original HIE Data Points ...	27
Figure 12. Effect of Average Coinsurance on Spending, by Type of Service ...	35
Figure 13. Effect of Coinsurance on Annual Per-Person Total Medical and Prescription Drug Expenses, as a Percentage of Free Plan Expenses ..	42

## List of Tables

Table 1. Estimated Pure Price Effects of Coinsurance on Medical Expenses, as a Percentage of Free Plan Expenses .....	16
Table 2. Arc Elasticities Between Average Coinsurance Amounts, by Type of Service .....	17
Table 3. Predicted Free-Plan Spending Using Arc Elasticities, by Elasticity Formula for Predicted Spending .....	19
Table 4. Induction Factors Between Average Coinsurance Amounts, by Type of Service .....	22
Table 5. Predicted Spending of Example Person in Plan With \$1,000 Deductible and 25% Coinsurance, Based on Predicted Free-Plan Spending, By Cost-Sharing Method .....	34
Table 6. Example Person's Predicted Spending at 95% Coinsurance, by Type of Service and Factor .....	36
Table 7. Average Predicted Spending, by Plan and Factor, Based on 2002 MEPS .....	38

# Alternatives for Modeling Results from the RAND Health Insurance Experiment

Changes in health insurance plans' cost-sharing (for example, the deductible and coinsurance) affect the quantity of health services used, according to results from the seminal RAND Health Insurance Experiment (HIE) of the 1970s and 1980s. Generally speaking, if a person's cost-sharing increases, less health care will be used; if cost-sharing decreases, more health care will be used. Economists account for such changes with a measure called a demand elasticity; actuaries have a related measure, called induction factors.

These two methods are used in health insurance models, usually with the purpose of replicating the HIE results. Neither of these methods is perfect or even perhaps inherently preferable. Moreover, converting the HIE results into appropriate elasticities or induction factors is not always straightforward. The use of each has benefits and shortfalls, but little comparative analysis has been done.

The Congressional Research Service (CRS) has partnered for more than a decade with actuaries from the Hay Group to formulate microsimulation models that provide estimates of the actuarial value of health insurance plans. To account for changes in cost-sharing, these models use induction factors. CRS and Hay are in the process of a significant overhaul of these models. As part of that process, the application of the models' induction factors was assessed and compared to elasticities and another alternative presented in this report, the cubic formula. This report is the documentation of that assessment.

This report begins with a basic explanation of elasticities and their health insurance applications. Induction factors are similarly described then contrasted with elasticities from a theoretical standpoint. Such an elementary explanation is intended to ensure that the key distinctions and limitations of elasticities and induction factors are not missed, particularly for their applications in modeling. The next section of the report reviews some of the key findings from the RAND Health Insurance Experiment. Finally, the report discusses how best to replicate HIE results using elasticities, induction factors, and the cubic formula.

In short, this report assesses the ability of the three methods to consistently replicate certain RAND Health Insurance Experiment results. Because health care and people's responsiveness to its costs may have changed in the decades since the HIE's implementation, the method that best replicates the HIE results may not in fact best represent current responsiveness to health care cost-sharing. Whether people's responsiveness has changed is difficult to know without another experimental study like the HIE. However, on the specific question of which method is best for replicating the HIE results, this report points to the cubic formula.

## Theoretical Explanation of Cost-Sharing Methods

### Elasticity of Demand

The elasticity of demand is a number that approximates the effect that a change in price has on the quantity purchased of a good or service. In other words, elasticities are used to answer this question: If the original quantity ( $Q_0$ ) of a good or service is purchased at the original price ( $p_0$ ), how many units would be purchased ( $Q_1$ ) at a different price ( $p_1$ )?

For two given prices ( $p_0$  and  $p_1$ ) and the two associated quantities ( $Q_0$  and  $Q_1$ ), the elasticity is defined as the percentage change in quantity resulting from a one percent change in price. Starting from a particular point ( $p_0, Q_0$ ), this is represented algebraically as follows:

$$(1) E_{\text{point}} = \frac{\frac{Q_1 - Q_0}{Q_0}}{\frac{p_1 - p_0}{p_0}}$$

For example, a car dealership knows that if its price on a particular model is \$30,000, it will sell 500 of those cars in the year; however, if it drops its price to \$27,000, it will sell 600. The point elasticity would then be calculated as follows:

$$(2) E_{\text{point}} = \frac{\frac{600 - 500}{500}}{\frac{27,000 - 30,000}{30,000}} = \frac{20\%}{-10\%} = -2$$

Because the absolute value of the elasticity is greater than one, it denotes that people are very responsive to price changes for this model. Specifically, a 10% drop in price would yield a 20% increase in quantity demanded.

Those dealing with elasticities aspire to apply a particular value, say -2, to all different prices and quantities for that good. However, point elasticities do not yield consistent results; as a cost-sharing factor, they lack certain desirable properties. One such property is reversibility, which means that the calculation of a cost-sharing factor (based on two points) yields the same result regardless of which point is considered the starting point ( $p_0, Q_0$ ). Point elasticities are not reversible, as demonstrated below by using the same two points used in Eq. (2) but switching the starting point. The elasticity below, -1.5, does not match the previous one, -2:

$$(3) E_{\text{point}} = \frac{\frac{500 - 600}{600}}{\frac{30,000 - 27,000}{27,000}} = -1.5$$

To obtain the same elasticity from a given pair of points, arc elasticities are used instead of point elasticities. In other words, arc elasticities are reversible. Arc

elasticities are calculated as (change in quantity divided by average quantity) / (change in price divided by average price), or:

$$(4) E_{\text{arc}} = \frac{\frac{Q_1 - Q_0}{(Q_1 + Q_0)/2}}{\frac{P_1 - P_0}{(P_1 + P_0)/2}}$$

Using the prior example, the arc elasticity is the following, and does not vary regardless of which is chosen as  $(p_0, Q_0)$ :

$$(5) E_{\text{arc}} = \frac{\frac{600 - 500}{(600 + 500)/2}}{\frac{27,000 - 30,000}{(27,000 + 30,000)/2}} = -1.73$$

As in this example, the arc elasticity (-1.73) is often close to the average of the point elasticities (-1.75).

In addition to reversibility, another advantage of the arc elasticity is that it is defined even if any of the parameters equals zero. In the point-elasticity formula, if either  $p_0$  or  $Q_0$  is zero, the elasticity cannot be calculated. For these reasons, arc elasticities are generally favored by health economists over point elasticities.

Although the arc elasticity may be nearly as easy to calculate, the point elasticity is often easier to apply when predicting quantity ( $Q_1$ ). Eq. (6) shows the formula that results from solving the point-elasticity formula in Eq. (1) for  $Q_1$ .

$$(6) Q_{1 \text{ point}} = Q_0 (1 + E(p_1 - p_0)/p_0)$$

Eq. (7) shows the formula that results from solving the arc-elasticity formula in Eq. (4) for  $Q_1$ .

$$(7) Q_{1 \text{ arc}} = Q_0 (E_{p_0} - E_{p_1} - p_1 - p_0) / (E_{p_1} - E_{p_0} - p_1 - p_0)$$

The temptation is to take an arc elasticity and predict  $Q_1$  based on the point-elasticity formula in Eq. (6). However, this does not yield proper results. To illustrate, apply the previously calculated arc elasticity (-1.73) to predict  $Q_1$  when  $p_1$  is \$27,000 and the starting point is (\$30,000, 500). Although the actual  $Q_1$  is 600, the point-elasticity version of  $Q_1$  yields 586. For the point-elasticity version of  $Q_1$  to yield 600, the original point elasticity of -2 would have to be used. Although it is more unwieldy, the arc-elasticity version of  $Q_1$  in eq. (7) yields the proper result (in this case, 600) when applying the arc elasticity.

In other words, when predicting quantity using elasticities, it is critical to use the  $Q_1$  formula that corresponds with the elasticity used, whether arc or point.<sup>1</sup> The additional complication of applying the point elasticity is that, because it is not reversible, one must determine which point elasticity to use; when predicting  $Q_1$  from a particular  $(p_0, Q_0)$ , it is best to choose the point-elasticity value based on the starting point closest to the one it is being applied to.

**Health Insurance Applications.** Calculating elasticities when individuals are covered by health insurance is complicated by the fact that the price paid by consumers for health care (that is, their cost-sharing) is usually not the full price of that care. For example, the average price of a hospital stay may be \$5,000, but the insured’s effective “price” would be only the cost-sharing — a \$750 deductible, for example. This effective price, the person’s out-of-pocket liability, is what influences their behavior rather than the total price. Thus, when looking at elasticities for health insurance purposes, the prices ( $p_0$  and  $p_1$ ) are generally the prices paid by the individual out of pocket rather than the actual total price for the good or service.

In addition, it is often difficult to measure the quantity of health care purchased. When deriving an elasticity for health care, what should be used for “quantity”? Fortunately, there is a way around this dilemma, using the fact that the *total* amount spent on health care (i.e., the person’s out-of-pocket payments plus payments by insurance) is the *actual* price of the good or service (not just the out-of-pocket amount) multiplied by the quantity used. Therefore, the percentage change in *total spending* would be as follows, with  $P_0$  and  $P_1$  representing the *actual* price of the good or service, not just the out-of-pocket amount:

$$(8) \quad \% \Delta \text{ in total spending} = \frac{P_1 Q_1 - P_0 Q_0}{P_0 Q_0}$$

However, in calculating elasticities based on cost-sharing changes, we assume that the *actual* price of the health good service does not change — that is, that  $P_0$  and  $P_1$  are equal. As such, price falls out of the equation so that the percentage change in total spending is equivalent to the percentage change in quantity demanded:

$$(9) \quad \% \Delta \text{ in total spending} = \frac{P Q_1 - P Q_0}{P Q_0} = \frac{Q_1 - Q_0}{Q_0} = \% \Delta \text{ in quantity demanded}$$

Thus, the easiest way empirically to calculate an elasticity for health care is to use the percentage change in total spending as the percentage change in quantity demanded. This applies to all of the uses of “quantity” for the remainder of this report.

For example, an insurance company contracts with physicians so that a typical office visit is \$100, or  $P$ . On average, its enrollees make three visits per year, for

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<sup>1</sup> It is possible to use an arc elasticity in the point-elasticity formula for  $Q_1$  and obtain the appropriate  $Q_1$  by using a multiplicative factor. However, calculating that factor is more cumbersome than simply using the appropriate formula in Eq. (7).



total spending of \$300 per enrollee for the office visits. The enrollees must pay a copayment per visit of \$5 (a coinsurance of 5%). The following year, the plan keeps its contract arrangements the same with physicians but increases its copayments to \$25 for office visits (a coinsurance of 25%). The result is that the average number of visits drops to 2.25, for total average spending of \$225. From these figures, the arc elasticity is calculated as follows:

$$(10) \ E_{\text{arc}} = \frac{\frac{225 - 300}{(225 + 300)/2}}{\frac{25 - 5}{(25 + 5)/2}} = -0.21429$$

Because the absolute value of this elasticity (0.21429) is less than one (and closer to zero), one would say the demand for this type of care is relatively inelastic. That is, a substantial change in the effective price of care led to a relatively small change in the amount of care demanded.<sup>2</sup>

Nevertheless, the example is a much-simplified version of the cost-sharing structure for the range of services in most health insurance plans, which have deductibles and out-of-pocket maximums in addition to copayments and coinsurance that may vary by type of service. As a result, precisely determining  $p_1$  for actual health insurance plans is not straightforward;  $p_1$  becomes a function not only of the new cost-sharing structure but of  $Q_1$ , the variable we seek to derive from  $p_1$ . Because of this simultaneous (some might say circular) relationship, elasticities appear to be limited outside of applications to plans with only coinsurance cost-sharing.<sup>3</sup>

## Induction Factors

Induction factors are not discussed as commonly as elasticities in health policy circles. A thorough literature review on the topic came up with only a handful of references, all several years old.<sup>4</sup> Like elasticities, induction factors are used to

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<sup>2</sup> With an explicit measure of quantity (number of visits), because the underlying total price (\$100) remained the same, the arc elasticity would yield the same result whether using that quantity or total spending, affirming what was shown in Eq. (9). From the two data points in this example, the point elasticities would be -0.0625 and -0.4167, depending on which point was chosen as the start. This is quite a large range for describing the impact of cost-sharing changes.

<sup>3</sup> A plan's average coinsurance is often estimated in an effort to make elasticities applicable, which is discussed later in this report.

<sup>4</sup> Daniel Zabinski et al., "Medical Savings Accounts: Microsimulation Results from a Model with Adverse Selection," *Journal of Health Economics*, volume 18 (1999), pp. 195-218. (Hereafter cited as Zabinski, et al., *Medical Savings Accounts*.) Edwin Husted et al., "Medical Savings Accounts: Cost Implications and Design Issues," American Academy of Actuaries' Public Policy Monograph No. 1, May 1995, at [[http://www.actuary.org/pdf/health/msa\\_cost.pdf](http://www.actuary.org/pdf/health/msa_cost.pdf)]. Husted is also the principal actuary at the Hay Group for the CRS contract on the valuation models. Documentation on those models regarding induction factors is very similar to the write-up in the MSA monograph.

(continued...)

predict the impact of cost-sharing changes on total health care spending. The key advantage of induction often touted over elasticities is that its factors are relatively easy to apply on all plan types, even those with complicated cost-sharing structures. “Moving beyond the simplified case of pure coinsurance, the actuarial method [of induction] offers a tractable, albeit imperfect, approximation to the actual change in medical care.”<sup>5</sup> It avoids elasticities’ circular conundrum by applying the new cost-sharing structure to the *original* spending. It does this by calculating the dollar amount of out-of-pocket payments (OOP) under the old and the new cost-sharing structures, holding total spending ( $Q_0$ ) constant. Where  $I$  is the induction factor and  $OOP_{1*}$  denotes the dollar amount paid out of pocket based on the *new* cost-sharing structure but the *old* quantity demanded,  $Q_1$  is predicted as follows:

$$(11) \\ Q_1 = Q_0 + I (OOP_0 - OOP_{1*})$$

Solving this equation for the induction factor yields the following:

$$(12) \\ I = (Q_1 - Q_0) / (OOP_0 - OOP_{1*})$$

Eqs. (11) and (12) illustrate that an induction factor is a very different measure from an elasticity, even though both may try to replicate similar impacts of cost-sharing changes on total health care spending. The value of an elasticity represents the percentage change in quantity resulting from a one percent change in price. The value of an induction factor is the percentage of the difference in two plans’ out-of-pocket payments that directly affects total health care spending.

For example, a person has total health care spending of \$5,000, of which \$4,000 is paid by a health insurance plan and \$1,000 out of pocket. Another plan in which the person had total spending of \$5,000 may require \$1,500 out of pocket, a \$500 increase. An induction factor of 70%, or 0.7, means that total health care spending would be reduced by 70% of the out-of-pocket difference between the plans (70% of \$500, or \$350). Thus, under the new plan with higher cost-sharing, total health care spending for the person would be predicted to drop to \$4,650 (that is, \$5,000 - \$350).

Although induction factors and elasticities are very different measures, there are cases in which they can be shown to be closely related. For example, in plans where the cost-sharing can be represented as a pure coinsurance, the induction formula’s  $OOP_{1*}$  can be written as  $Q_0 p_1$ , and  $OOP_0$  as  $Q_0 p_0$ . In that case, Eq. (11) can be written as shown in Eq. (13), which can be solved for the induction factor, as shown in Eq. (14):

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<sup>4</sup> (...continued)

“Methodological Description of Health Care Reform Premium and Discount Estimates,” addendum to The White House Domestic Policy Council, “Health Security Act: The President’s Report to the American People,” Oct. 1993, at [<http://www.ibiblio.org/pub/academic/medicine/Health-Security-Act/supporting-documents/method2.txt>].

<sup>5</sup> Zabinski et al., *Medical Savings Accounts*, p. 200.

$$(13) \quad Q_1 = Q_0 + Q_0 I(p_0 - p_1)$$

$$(14) \quad I = \frac{\frac{Q_1 - Q_0}{Q_0}}{p_0 - p_1}$$

The following emerges by dividing both the numerator and denominator of the right-hand side of Eq. (14) by  $-p_0$ :

$$(15) \quad I = \frac{\frac{Q_1 - Q_0}{Q_0}}{\frac{p_1 - p_0}{p_0}} \times \frac{-1}{p_0} = -E_{\text{point}} / p_0$$

Through similar algebraic manipulations, the induction factor can also be written as follows:

$$(16) \quad I = -E_{\text{arc}} (Q_1 + Q_0) / [Q_0(p_1 + p_0)]$$

These last two equations may not have widespread practical applications. However, they both illustrate that induction factors can be expressed as a function of elasticities, both point and arc, in their pure coinsurance forms.<sup>6</sup> They also highlight an issue that is indicated by the  $Q_0$  in the denominator of Eq. (16) and in the upper denominator of Eq. (14) — that induction factors are not reversible. That is, induction factors calculated from two points will yield different values depending on which of the two points was chosen as the starting point. This is the same shortcoming that point elasticities have, and Eq. (15) does not fix this. Arc elasticities do not have this shortcoming, thus the induction-factor equation as a function of the arc elasticity in Eq. (16) necessarily places  $Q_0$  in the denominator to introduce it. Because two values for the induction factor result from any two price-quantity data points, care must be taken to choose the correct one, depending on the  $Q_0$  used to create the factor *and* the  $Q_0$  used to predict cost-sharing changes in a new plan.

**Health insurance applications.** Using the office-visit example presented earlier, Eq. (14) yields the following induction factor:<sup>7</sup>

$$(17) \quad I = \frac{\frac{225 - 300}{300}}{5\% - 25\%} = 1.25$$

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<sup>6</sup> Zabinski et al., *Medical Savings Accounts*, shows another version of the induction factor as a function of the arc elasticity.

<sup>7</sup> Eqs. (12), (15) and (16) also yields an induction factor of 1.25.

Induction factors' lack of reversibility is demonstrated once more by reversing the parameters of the office-visit example and calculating that induction factor:

$$(18) I = \frac{300 - 225}{25\% - 5\%} = 1.67$$

In sum, although induction factors appear to enable a better analysis of a greater variety of health insurance plans, compared to arc elasticities, they are not unambiguously superior — one reason being that they are not reversible. Specifically, the use of induction factors could lead to flawed results if a single value is being used across a domain of coinsurance levels.

## Additional Comparisons

In elementary algebra, the slope of a line is defined as rise over run — specifically, the change in the dependent variable (y) divided by the change in the independent variable (x). Thus, the equation for the linear slope between two price-quantity data points is  $(Q_1 - Q_0)/(p_1 - p_0)$ .<sup>8</sup> Substituting this in the cost-sharing formulas previously discussed yields the following:

$$(19) E_{\text{point}} = \text{slope} * (p_0 / Q_0)$$

$$(20) E_{\text{arc}} = \text{slope} * (\text{average } p) / (\text{average } Q)$$

$$(21) I = \text{slope} / -Q_0$$

Interestingly, if the predicted quantity (say,  $Q_2$ ) based on some price ( $p_2$ ) is calculated from a starting point ( $p_0, Q_0$ ) based on one of the original points used to calculate the factors above, the equation is reduced to the following for both point elasticities and induction factors:

$$(22) Q_2 = Q_0 + \text{slope} * (p_2 - p_0)$$

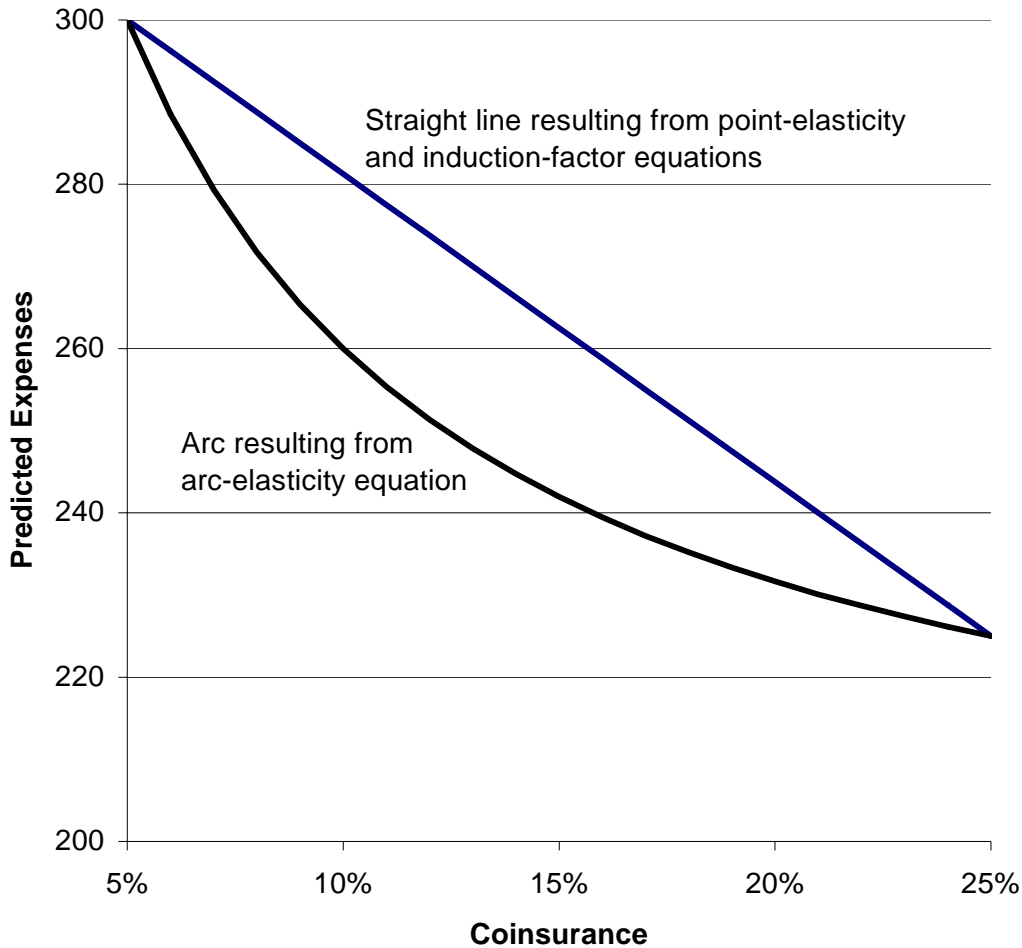
This results in a straight line with the original slope and passing through the original data points.<sup>9</sup> From the office-visit example, moving from 5% to 25% coinsurance yields an induction factor of 1.25 and a point elasticity of -0.0625. Applying these factors in the domain of 5% to 25% coinsurance to predict quantity yields the straight line in **Figure 1**, as Eq. (22) would predict.

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<sup>8</sup> Economists tend to flip the axes when dealing with price and quantity to create a demand curve with a slope that is the reciprocal of this one. For this report, traditional graphs and slopes are used, with apologies to economists who would prefer straightforward demand curves.

<sup>9</sup> The derivative of  $Q_2$  with respect to  $p_2$  yields the original slope.

**Figure 1. Predicted Expenses Using Various Cost-Sharing Methods, from Example Case**



**Source:** Congressional Research Service (CRS) example and calculations.

This characteristic has important implications for applying the RAND HIE results, discussed later.<sup>10</sup> However, similarly substituting Eq. (20) in the predicted-quantity formula for arc elasticities, Eq. (7), does not yield a simplified equation of any sort.<sup>11</sup> Using the arc-elasticity formulas, predicted quantity yields a non-linear curve — an arc. That arc will pass through the original pair of data points if the starting point ( $p_0, Q_0$ ) used to predict quantity is one of the original data points. The

<sup>10</sup> The same line results when switching the starting point of the two original data points *and* when using the appropriate, other point elasticity or induction factor.

<sup>11</sup> In lieu of using the substitution of the slope, calculus can be used to find some simplified form for the predicted quantity based on the arc-elasticity formula. Let Eq. (7) predict a  $Q_2$  based on some  $p_2$ , given a constant elasticity calculated from two original data points. The derivative of  $Q_2$  with respect to  $p_2$  yields a complicated equation. The gist of the resulting equation is that  $p_2$  appears only in the denominator, as a quadratic formula. This is consistent with the arc that results from applying Eq. (7), as in **Figure 1**.

arc in **Figure 1** illustrates this for the coinsurance domain of 5% to 25%, using (5%, 300) as the starting point and -0.21429 as the arc elasticity.

The concavity of the arc also indicates that responses to cost-sharing will not be constant, as is the case using point elasticities and induction factors. Specifically, the concavity results in greater responsiveness at lower prices than at higher prices, within the applicable domain. Whether this is preferable to a constant responsiveness probably depends on the good or service being analyzed. With respect to the demand for health care, this concavity is consistent with the HIE results discussed later — that people are more responsive to cost-sharing changes when their cost-sharing is relatively small, compared to the response when their cost-sharing is higher.

Another desirable property of cost-sharing factors in addition to those mentioned earlier is path neutrality — that is, when using a factor's particular value (based on two data points), the *predicted quantity* for a given price should be identical regardless of which point is chosen as the start ( $p_0, Q_0$ ).<sup>12</sup> For example, the straight line in **Figure 1** (from induction factors and point elasticities) results whether using (5%, 300) or (25%, 225) as the starting point. However, in spite of the reversibility of the underlying factor, arc elasticities are not path neutral. The arc in **Figure 1** would be slightly different had (25%, 225) been used as the starting point. Beginning at the higher price, the resulting arc would not bulge as much from the straight line. At 15% coinsurance, for example, the quantity at the straight line is 262.5; on the arc in **Figure 1**, it is 241.9; if the starting point had been (25%, 225), the quantity on the arc would have been at 250.5. At 15% coinsurance, the difference in the estimated quantity between the arc-elasticity results is approximately 3.5%.

In the previous examples, the starting point ( $p_0, Q_0$ ) used to predict quantity has always been one of the two original points used in calculating the cost-sharing factor. However, when applying a given cost-sharing factor, the data may require beginning from a known point that is not one of the original points (if those original points were even known). In the office-based example — given the induction factor of 1.25, the point elasticity of -0.0625, and the arc elasticity of -0.21429 — assume a plan has 15% coinsurance ( $p_0$ ) and that an analyst wants to predict a range of quantities based on changes to that coinsurance. If a cost-sharing factor is path neutral, then the predicted quantities in this example should be the same as illustrated in **Figure 1**. Assuming this would be the case, the  $Q_0$  associated with the 15% coinsurance was taken from the points on the lines in **Figure 1** — 262.5 for the point-elasticity and induction formulas, and 241.9 for the arc-elasticity formula.

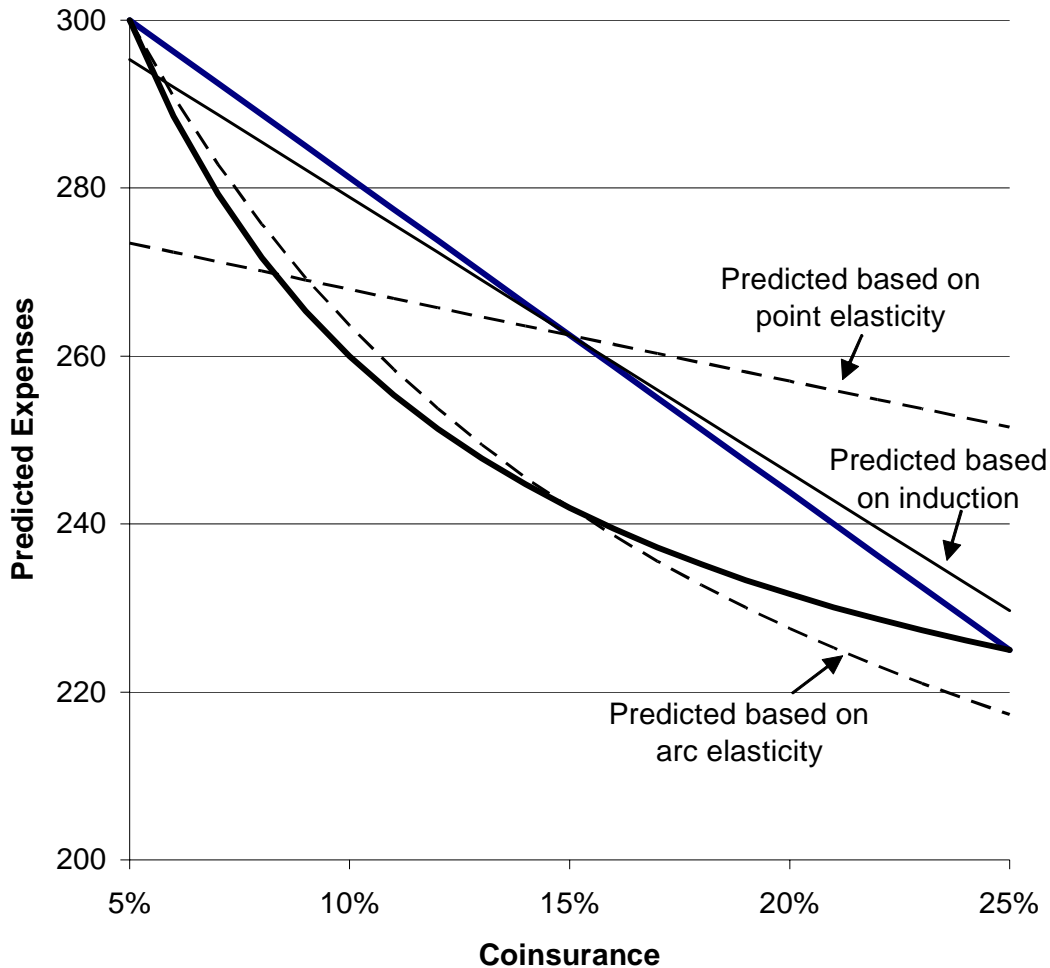
**Figure 2** shows the predicted quantities generated from a beginning coinsurance of 15% and applying the various cost-sharing methods. The dark lines are the original ones from **Figure 1** with which the results would coincide if they were path neutral. However, none of the three cost-sharing methods — point elasticities, induction factors or arc elasticities — is path neutral. The dashed lines show the predicted quantities based on the elasticities, with the straight line based on the point elasticity and the arc based on the arc elasticity; the light, solid line shows the

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<sup>12</sup> Tom Selden, an economist at the Agency for Healthcare Research and Quality (AHRQ), came up with this name for the concept.

predicted quantities based on the induction factor. All of the methods reproduce the  $Q_0$  on which the predicted quantities in the figure were based, at 15% coinsurance. Only the arc elasticity matches the original data point (5%, 300). Note that none of the methods obtains the original point of (25%, 225).<sup>13</sup> This lack of path neutrality is a serious limitation of all these cost-sharing methods, the implications of which are discussed in detail in the section on the methods' ability to replicate HIE results.

**Figure 2. Predicted Expenses Using Various Cost-Sharing Methods and Values, from Example Case Results at 15% Coinsurance**



**Source:** Congressional Research Service (CRS) example and calculations.

**Note:** The two dark lines are the original results shown in **Figure 1**. Ideally, the factors would be path neutral; because they are not, each of the three factors yields predicted quantities that do not coincide with the original lines. See text for description of results.

<sup>13</sup> As demonstrated previously, arc elasticities are not path neutral even when using one of the factor's original points as the starting point for predicting quantity. The other predicted quantity associated with 15% coinsurance ( $Q_0=250.5$ ) would have yielded yet another distinct arc in **Figure 2**, this one passing through the original point of (25%, 225) but not (0%, 300).

## RAND Health Insurance Experiment

The RAND Health Insurance Experiment (HIE) was ongoing from the mid-1970s to the early 1980s. Two thousand nonelderly families from six urban and rural areas were randomly assigned health insurance plans with different levels of cost-sharing. The results from this unprecedented health insurance experiment showed that people facing higher cost-sharing (that is, they had to pay a higher proportion of total health care costs out of their own pockets) had lower health care spending than those in plans with lower cost-sharing. No similar experiment has been performed since the HIE, so it remains the epochal analysis for understanding the link between health insurance cost-sharing and total health care spending.

The key variable used to explain health care spending in the HIE was the plans' coinsurance — that is, the *percentage* of total health care costs that the individual must pay. Four coinsurance rates were used: 0% (called the free plan, in terms of there being no cost-sharing), 25%, 50%, and 95%. However, for each coinsurance rate, there were three plans, each with a different out-of-pocket maximum: 5%, 10%, or 15% of family income, up to a maximum of \$1,000.<sup>14</sup> A person may have been enrolled in the “25% coinsurance plan,” but after that person reached the out-of-pocket maximum, the plan effectively became a 0% coinsurance plan. Thus, the HIE results need to be understood in the context of other variables besides the nominal coinsurance, particularly the out-of-pocket maximum.

### Selected Results

From the HIE data, the RAND authors calculated annual per-person medical spending, controlling for factors such as location and factors that affect likelihood of having a medical expense.<sup>15</sup> These results are shown in **Figure 3** for the four coinsurance levels (incorporating all the out-of-pocket maximums), with the four points connected by line segments.

As shown in the figure, average free-plan spending was \$1,019 (in 1991 dollars). Plans with a nominal coinsurance of 25% averaged \$826 in spending, significantly less than in the free plan ( $p < 0.001$ ). At the 50% nominal coinsurance level, spending averaged \$764, significantly less than in the 25% plans ( $p = 0.05$ ,  $t = 1.97$ ). Plans with a nominal coinsurance of 95% averaged \$700 in spending, less than in the 50% plans ( $p = 0.06$ ,  $t = 1.93$ ). Note that for the remainder of this report, many results are shown rounded, even if their usage later on is based on the unrounded amounts. This may cause others' results to differ slightly.

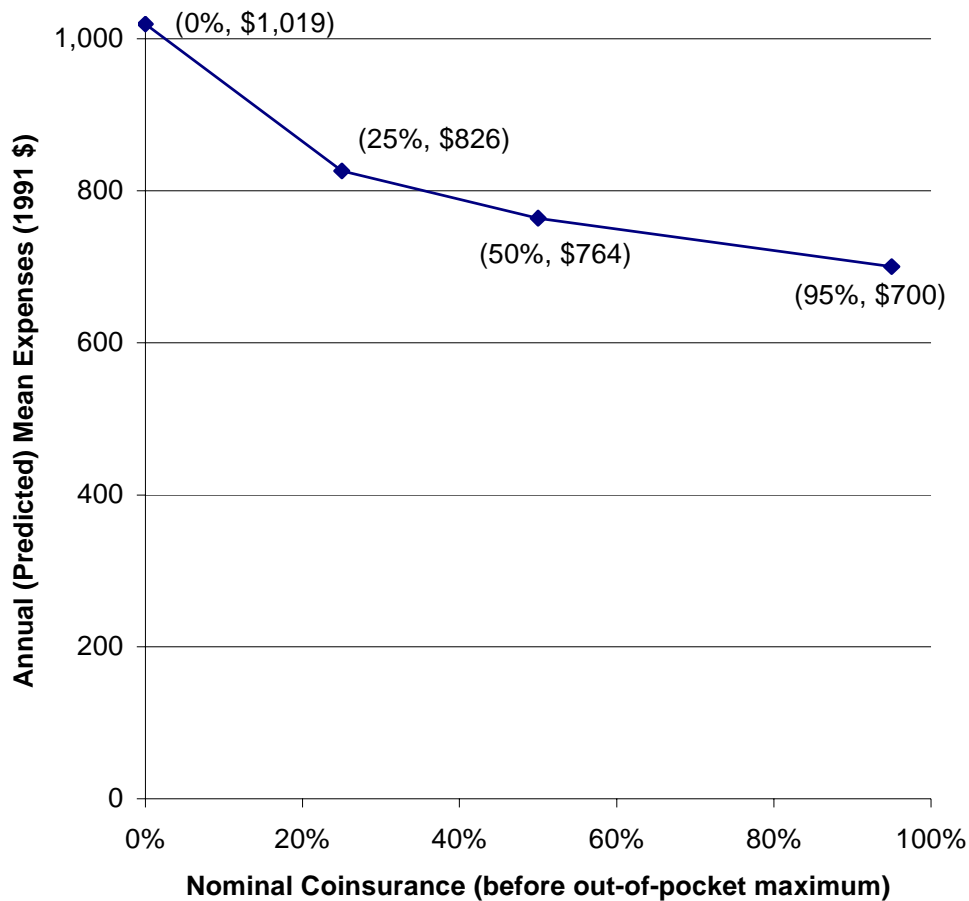
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<sup>14</sup> More information on the design of the experiment is available from many sources, including Joseph P. Newhouse et al., *Free for All? Lessons from the RAND Health Insurance Experiment* (Cambridge, Massachusetts: Harvard University Press, 1993). (Hereafter cited as Newhouse, *Free for All?*). Authors of the HIE often refer to the out-of-pocket maximum as the Maximum Dollar Expenditure (MDE). There were a couple other plans with slightly different cost-sharing designs, but they received less attention in the HIE results.

<sup>15</sup> All of the results in this section are based on the average annual per-person medical spending based on the four-equation model, described in Chapter 3 of Newhouse et al.



**Figure 3. Effect of Nominal Coinsurance on Annual Per-Person Medical Expenses, in Dollars, from RAND Health Insurance Experiment**



**Source:** Table 3.3, Joseph P. Newhouse et al., *Free for All? Lessons from the RAND Health Insurance Experiment* (Cambridge, Massachusetts: Harvard University Press, 1993).

**Note:** Expenses exclude dental and outpatient psychotherapy. For each coinsurance rate, there are multiple plans, each with its own out-of-pocket maximum (none exceeding \$1,000).

Because the dollar amounts are for 1991, it is useful to standardize the results, with the free-plan spending (\$1,019) as the base for comparing health care spending. Spending in the 25% coinsurance plan would be represented as having 81% of the free-plan spending, and so on. This is shown by the points connected by the heavy solid line segments in **Figure 4**.

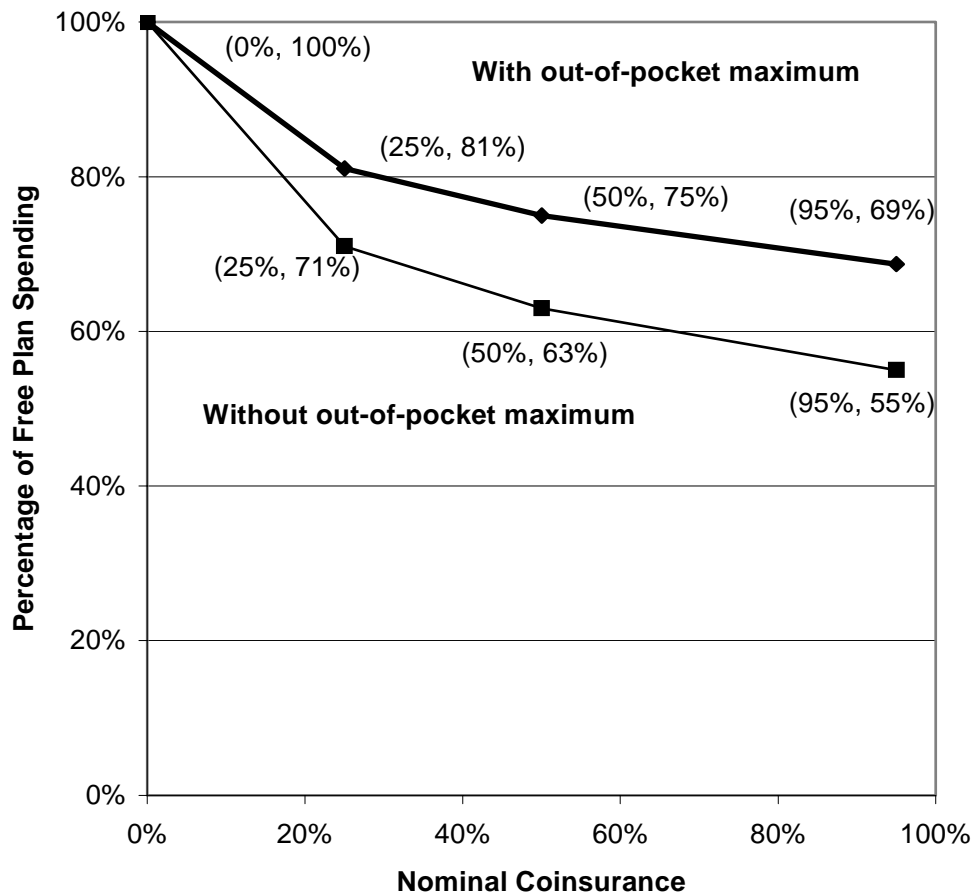
As previously mentioned, the effect of the plan's coinsurance is diminished by its particular out-of-pocket maximum. The RAND authors noted, for example, "individuals who exceeded the [out-of-pocket maximum] tended to increase their spending on all [health care] episode types."<sup>16</sup> The authors then took steps to estimate the "pure price effect" of the coinsurance, estimating how much spending

<sup>16</sup> Newhouse et al., *Free for All?*, p. 105.

would occur in each coinsurance in the absence of any deductibles or out-of-pocket maximums. This is shown in **Figure 4** by the points connected by the lighter solid line segments.

As expected, average health care spending at a given coinsurance rate is lower if there is no out-of-pocket maximum, compared to levels with an out-of-pocket maximum. These estimates are from Table 4.17 of Newhouse et al., in which Chapter 4 provides a detailed description of how these estimates were obtained.

**Figure 4. Effect of *Nominal* Coinsurance on Annual Per-Person Medical Expenses, as a Percentage of Free Plan Expenses**



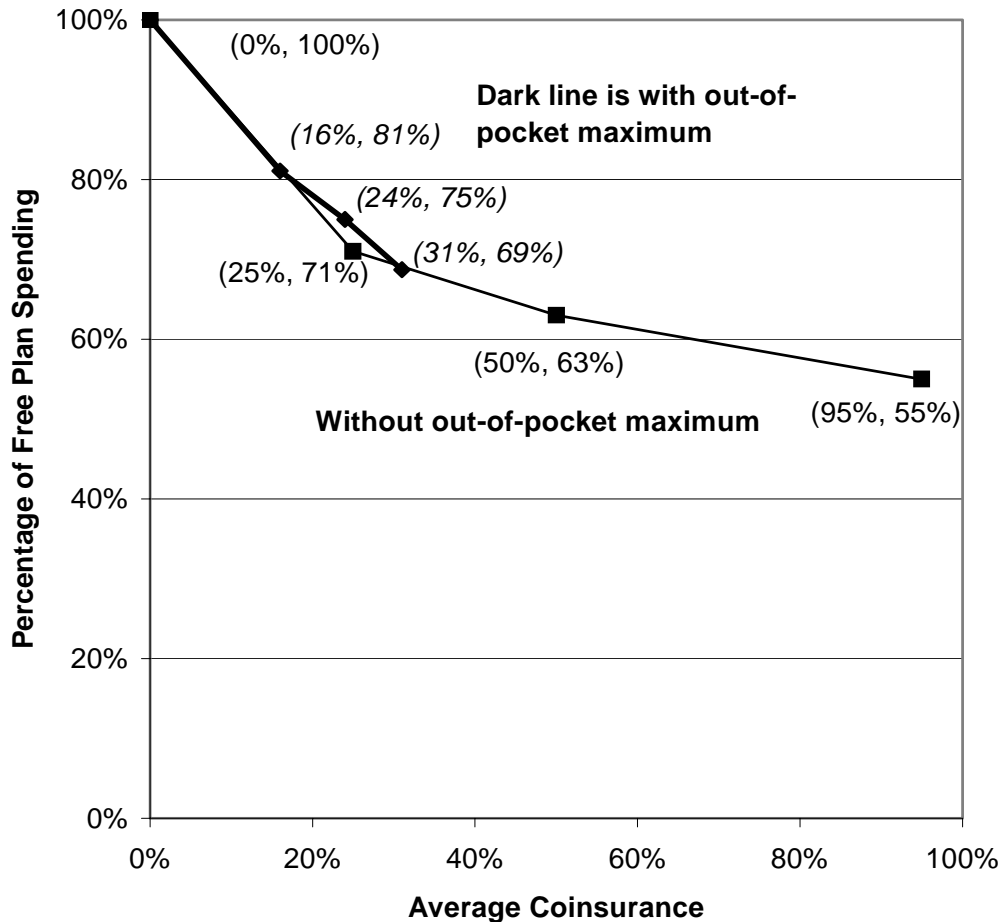
**Source:** Tables 3.3 and 4.17, Joseph P. Newhouse et al., *Free for All? Lessons from the RAND Health Insurance Experiment* (Cambridge, Massachusetts: Harvard University Press, 1993).

**Note:** Expenses exclude dental and outpatient psychotherapy. For each coinsurance rate, there are multiple plans, each with its own out-of-pocket maximum (none exceeding \$1,000).

Using only the nominal coinsurance from plans with an out-of-pocket maximum to estimate total spending raises concerns, since it overlooks the plan's out-of-pocket maximum, which can have a large impact on total spending, as illustrated in **Figure 4**. An alternative is to calculate the average coinsurance individuals faced in the plans. For example, a person with \$10,000 in spending in the typical HIE 25% plan would not have had \$2,500 in out-of-pocket spending; because the HIE plans limited

out-of-pocket expenditures, the most the person would have spent out of pocket was \$1,000. Had the person's out-of-pocket expenditure been \$1,000, the average coinsurance would have been 10%, not the nominal 25%. Because it reflects all cost-sharing (nominal coinsurance as well as deductibles and out-of-pocket maximums), the average coinsurance, rather than the nominal coinsurance, is arguably a preferable single value for representing a plan's overall cost-sharing.

**Figure 5. Effect of Average Coinsurance on Annual Per-Person Medical Expenses, as a Percentage of Free Plan Expenses**



**Source:** From the preceding figure, except the average coinsurance for plans with an out-of-pocket maximum is from Table 9, Willard G. Manning et al., "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment," *The American Economic Review*, vol. 77, no. 3 (June 1987), pp. 251-277.

**Notes:** Compare the dark line in this figure to the dark line in the preceding figure. The only difference is that the x-values in **Figure 4** are based on the *nominal* coinsurance while in this figure they are based on the *average* coinsurance. Over its applicable domain, the *average* coinsurance for plans with an out-of-pocket maximum yields spending in line with the pure price effects from pure-coinsurance plans. For pure-coinsurance plans, the nominal coinsurance is equal to the average coinsurance. Expenses exclude dental and outpatient psychotherapy.

Using the HIE data, the 25% plans' average coinsurance is 16%, the 50% plans' is 24%, and the 95% plans' is 31%. This is shown by the points connected by the heavy solid line segments in **Figure 5**, along with the previous points from the pure price effects (that is, for pure-coinsurance plans) from **Figure 4**. Over its applicable domain, the average coinsurance for plans with an out-of-pocket maximum yields spending in line with the pure price effects from pure-coinsurance plans.<sup>17</sup>

The concordance of these results is what one might have expected. It also makes applying these results convenient. First, microdata on health care expenditures rarely provide cost-sharing information like a plan's nominal coinsurance. The results in **Figure 5** suggest that such information may not be necessary — that the average coinsurance paid by a person, even in a plan with a complicated cost-sharing structure, should be as reliable in deriving and applying cost-sharing factors as that of a pure-coinsurance plan.

In addition, the average coinsurance of the typical HIE plans did not exceed 31%. However, in dealing with individuals' expenditure data, some people may have faced high cost-sharing. For example, many people may have had health care expenses that never reached their plan's deductible, thus facing an average coinsurance of 100%. Cost-sharing factors calculated from the HIE at an average coinsurance of 31% may not be appropriate when applied at 100% coinsurance. Because the pure price effects are estimated for coinsurance up to 95% and are consistent with the typical HIE plans through their average coinsurance domain of 31%, one can justify using cost-sharing factors from the pure price effects for application to all average coinsurance levels, regardless of the complexity of a plan's underlying cost-sharing structure.

Because of the potentially broader application of the HIE's estimated pure price effects, **Table 1** is provided, which shows these effects for outpatient and inpatient care as well as the total. It is worth noting that for up to 25% coinsurance, spending does not differ by outpatient versus inpatient care, relative to free-plan spending.

**Table 1. Estimated Pure Price Effects of Coinsurance on Medical Expenses, as a Percentage of Free Plan Expenses**

Pure coinsurance	Outpatient	Inpatient	Total medical	Dental
0%	100%	100%	100%	100%
25%	71%	71%	71%	79%
50%	58%	68%	63%	68%
95%	49%	60%	55%	50%

**Source:** Table 4.17, Joseph P. Newhouse et al., *Free for All? Lessons from the RAND Health Insurance Experiment* (Cambridge, Massachusetts: Harvard University Press, 1993).

**Note:** Computed assuming estimates weighted by shares of spending occurring when enrollees are far from reaching the plans' out-of-pocket maximum. For total medical, the shares are 46% outpatient and 54% inpatient.

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<sup>17</sup> For pure-coinsurance plans, the nominal coinsurance is equal to the average coinsurance.

## Calculating and Applying Cost-Sharing Methods Based on HIE Results

In this section of the report, cost-sharing factors (arc elasticities and induction factors) are calculated from the HIE results in **Table 1**.<sup>18</sup> In this section, once the arc elasticities and the induction factors are calculated, variations in their application and the results are discussed.

One goal of this analysis is to demonstrate how the factors might be applied in a microsimulation model, using the structure of the CRS/Hay models as an example. The CRS/Hay models use expenditure data from individuals who are enrolled in health insurance plans with innumerable (and unknown) cost-sharing structures. Using the expenditure data by source of payment (that is, out-of-pocket versus insurance-paid expenses), the first step is to standardize the data, applying cost-sharing factors to produce expenditure levels as if everyone were in a free plan. The estimated free plan data then becomes the baseline against which cost-sharing arrangements are applied.

**Table 2. Arc Elasticities Between Average Coinsurance Amounts, By Type of Service**

Average coinsurance range	Outpatient	Inpatient	Total medical	Dental
0% - 25%	-0.17	-0.17	-0.17	-0.12
0% - 50%	-0.27	-0.19	-0.23	-0.19
0% - 95%	-0.34	-0.25	-0.29	-0.33
0% - 25%	-0.17	-0.17	-0.17	-0.12
25% - 50%	-0.30	-0.06	-0.18	-0.22
50% - 95%	-0.27	-0.20	-0.22	-0.49
25% - 95%	-0.31	-0.14	-0.22	-0.39

**Source:** Congressional Research Service (CRS) calculations on data in **Table 1**, which is from Table 4.17, Joseph P. Newhouse et al., *Free for All? Lessons from the RAND Health Insurance Experiment* (Cambridge, Massachusetts: Harvard University Press, 1993).

### Arc Elasticities

**Table 2** displays the arc elasticities calculated according to Eq. (4) and based on the coinsurance ( $p_0$  and  $p_1$ ) and spending levels ( $Q_0$  and  $Q_1$ ) in **Table 1**. The first three rows show the arc elasticities when compared to the free plan. The next three display the arc elasticities between consecutive coinsurance rates. The last row shows the arc elasticity between 25% and 95% coinsurance.

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<sup>18</sup> Point elasticities are no longer in the discussion for a couple reasons. First, one of the four coinsurance levels used in the HIE is 0%, a value which makes the point-elasticity formula undefined. When the point elasticity performs best, its results coincide with those using induction factors. Otherwise, as illustrated in **Figure 2**, the application of the point elasticity is far from optimal.

The key column in **Table 2** is the shaded one showing elasticities for “total medical.” These values vary, depending on the average coinsurance range used.<sup>19</sup> Even if an analyst were to carefully select an elasticity according to these results, choosing a value is not always straightforward. Consider a person in a plan with 15% pure coinsurance on \$5,000 total spending (\$750 out of pocket). Which elasticity should be used if estimating the impact of moving to a 40% coinsurance plan? An elasticity of -0.22 would predict total spending at \$4,097, using Eq. (7). If an elasticity of -0.17 were used, total spending in the new plan would be estimated at \$4,284, nearly 5% higher. Thus, even the most fastidious analysts can reasonably use different elasticities and come up with different results on that basis alone.

**Predicting Quantity with Point-elasticity and Arc-elasticity Formulas.** Earlier in this report, it was noted that “when predicting quantity using elasticities, it is critical to use the  $Q_1$  formula that corresponds with the elasticity used, whether arc or point.” This point merits repeating in the context of the HIE results because arc-elasticity factors are so often applied in the point-elasticity formula for predicting quantity. That is, arc-elasticity factors like those in **Table 2** are often applied in Eq. (6) instead of the more appropriate Eq. (7).

Based on the total medical elasticities in **Table 2**, **Table 3** shows the results if one were to use those elasticities to estimate free-plan spending from the other three coinsurance rates. Specifically, for each row in **Table 3**, the appropriate elasticity is taken from the first three rows of **Table 2**. Since the purpose of the calculation is to estimate free-plan spending, the result should be 100%. Because the arc-elasticity formula is rarely written in terms of  $Q_1$ , arc elasticities are often applied using the point-elasticity formula in Eq. (6). Those results are shown in Column A of **Table 3** and do not yield the target amount of 100% shown in Column C. Column B shows the results of using the arc elasticities with the formula for  $Q_1$  from Eq. (7), which yields the targeted results. Eq. (23) illustrates how these results were calculated, applying the 0%-95% elasticity to the point-elasticity formula; Eq. (24) does the same but applies the elasticity in the arc-elasticity formula. The results in **Table 3** again illustrate why arc elasticities should not predict quantity using the point-elasticity formula. Although the arc-elasticity formula for predicting quantity is more complicated than the point-elasticity one, it is the correct one.

(23)

$$Q_1 = Q_0 (1 - E), \text{ where Eq. (6) is reduced because } p_1=0 \\ = 55\% (1 + 0.29) = 71\%$$

(24)

$$Q_1 = - Q_0 (E - 1) / (E + 1), \text{ where Eq. (7) is reduced because } p_1=0 \\ = - 55\% (-0.29 - 1) / (-0.29 + 1) = -55\% (-1.29)/(0.71) \\ = 100\%$$

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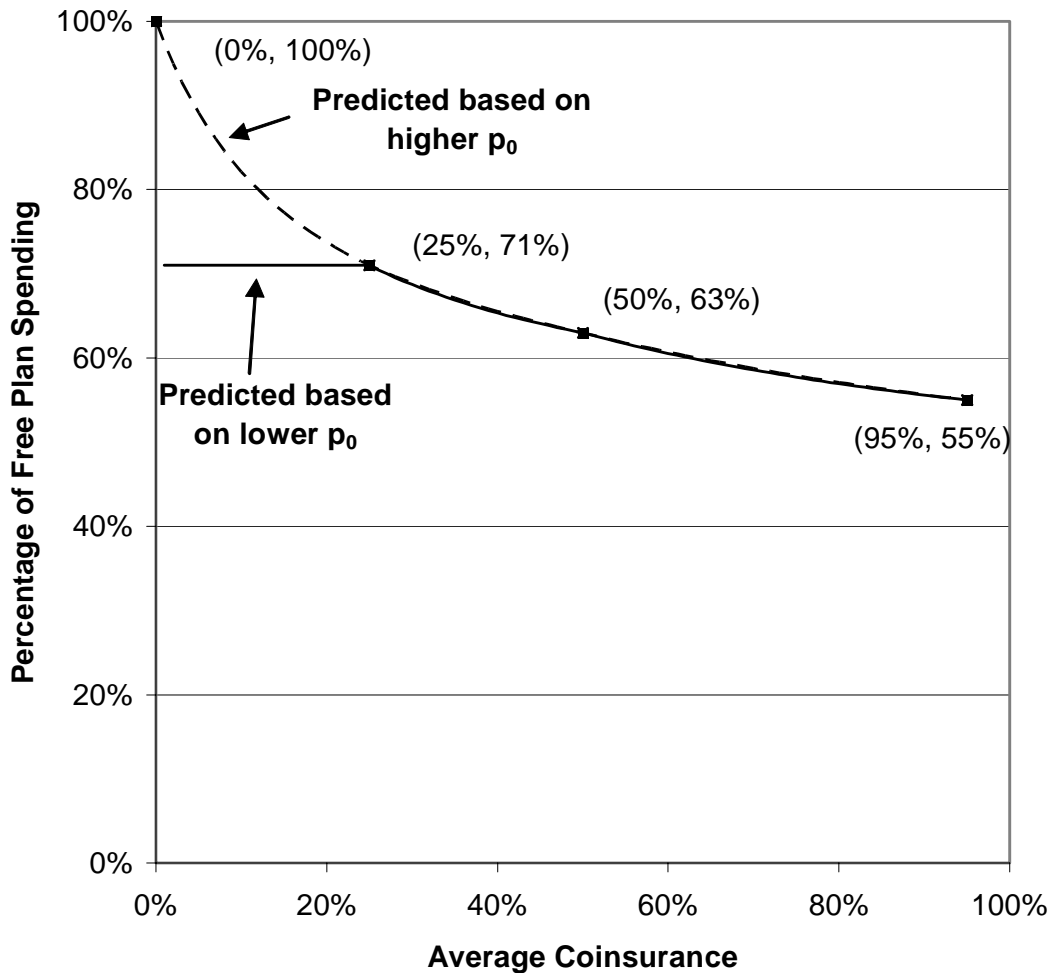
<sup>19</sup> The variation in this column tends to be smaller than that in the service-specific columns. The total medical elasticities reflect the combination of outpatient and inpatient spending and therefore have the result of tempering the differences in those elasticities.

**Table 3. Predicted Free-Plan Spending Using Arc Elasticities, by Elasticity Formula for Predicted Spending**

Beginning Coinsurance ( $p_0$ )	A	B	C
	Applying point-elasticity formula for total spending	Applying arc-elasticity formula for total spending	Target amount for total spending
25%	83%	100%	100%
50%	77%	100%	100%
95%	71%	100%	100%

Source: Congressional Research Service (CRS) calculations, using arc elasticities from **Table 2** and quantities from **Table 1**.

**Figure 6. Analysis of Arc Elasticity’s Lack of Path Neutrality in HIE Results: Predicting Quantity Varying By Beginning HIE Data Point**



Source: Congressional Research Service (CRS) analysis.

**Effect of Arc Elasticity's Lack of Path Neutrality.** As previously mentioned, the arc-elasticity formula for predicting quantity is not path neutral — that is, when using a factor's particular value (based on two data points), the predicted quantity for a given price will vary depending on which point is chosen as the start ( $p_0, Q_0$ ). Using the HIE data points as ( $p_0, Q_0$ ) and the appropriate elasticities between consecutive points yields the two curves in **Figure 6**.

The dashed line in the figure is predicted quantity based on the higher of two consecutive HIE data points. For example, if predicting quantity at a coinsurance price of 70%, this is between the HIE data points of (50%, 63%) and (95%, 55%), where the arc elasticity for total medical care is -0.22.<sup>20</sup> Using Eq. (7) and (50%, 63%) as ( $p_0, Q_0$ ) predicts a quantity of 58.6%. Using the same equation but the beginning point of (95%, 55%) predicts a quantity of 58.8%. This is a relatively small difference. In fact, over the domain of 25% to 95%, the difference in the predicted quantities, varying which pair of consecutive points is chosen as ( $p_0, Q_0$ ), averages about two-tenths of one percent.<sup>21</sup> This is shown graphically in **Figure 6** by the nearly imperceptible difference between the lines over the 25% to 95% domain.

**Figure 6** also illustrates a serious limitation of predicting quantity using an arc elasticity when the price is zero (that is, free), as was the case in the RAND Health Insurance Experiment. Applying the free-plan data from **Table 2** to predict quantity between a price of 0% and 25% coinsurance causes Eq. (7) to be reduced as follows:

$$\begin{aligned}
 (25) \\
 Q_1 &= Q_0(Ep_0 - Ep_1 - p_1 - p_0) / (Ep_1 - Ep_0 - p_1 - p_0), \text{ where } p_0=0 \text{ and } Q_0=1 \\
 &= (-Ep_1 - p_1) / (Ep_1 - p_1) \\
 &= \frac{1 + E}{1 - E}, \text{ where } E = -0.17 \\
 &= 71\%
 \end{aligned}$$

The constant predicted quantity of 71% is shown by the horizontal solid line over the 0% to 25% domain in **Figure 6** for the predicted quantity based on the lower  $p_0$ . Using a constant arc elasticity to predict quantity where price (either  $p_0$  or  $p_1$ ) is zero yields a constant quantity across the domain of prices. This is unacceptable for the present structure of the CRS/Hay models, which derive their results from a baseline of free-plan values.<sup>22</sup> Even analysts not predicting free-plan values must cope with this issue where a person's average coinsurance is 0%.

<sup>20</sup> In predicting quantity, the unrounded elasticity was used.

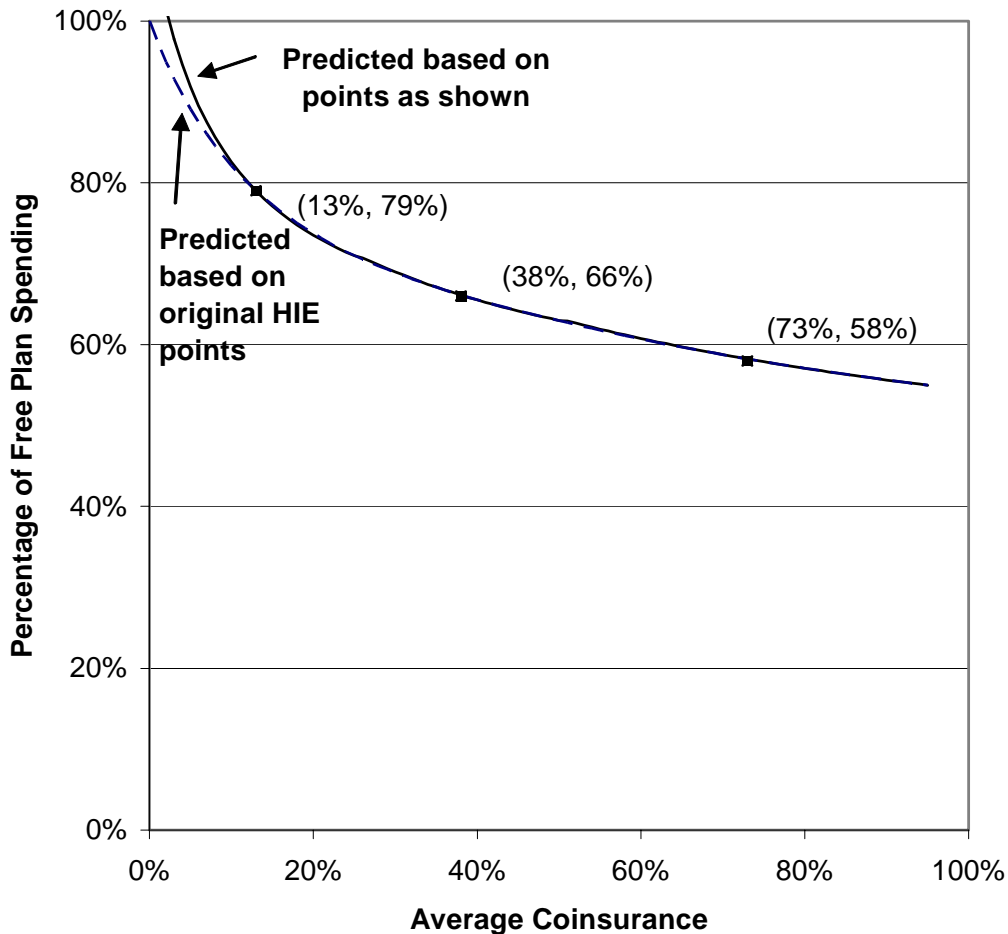
<sup>21</sup> This is determined by calculating the percentage difference in the integrals of Eq. (7) alternating the consecutive pairs of HIE points for the beginning point:  
 $\int Q_0(Ep_0 - Ep_1 - p_1 - p_0) / (Ep_1 - Ep_0 - p_1 - p_0) dp_1$   
 where  $E, Q_0$  and  $p_0$  are constants based on the HIE data, over the domain between the two HIE data points.

<sup>22</sup> It is not possible to apply the point-elasticity formula for total spending because  $p_0=0$ , making Eq. (6) undefined. It is also not advisable to use, for example, (1%, 99%) instead of (0%, 100%) because the shape of the resulting curve is not intuitive.



It was illustrated in **Figure 2** that using a  $(p_0, Q_0)$  that was not one of the original data points created a separate arc that did not line up with either of those based on the original data points. This is another potential area of concern for applying the arc elasticities. However, this appears to be less of a practical concern when using arc elasticities derived from the HIE results. The dashed line in **Figure 7** is the same one in **Figure 6**. The difference between the figures is that in **Figure 7** the solid line is based on the  $(p_0, Q_0)$  points shown in the figure, which are on the dashed line.

**Figure 7. Illustration of Arc Elasticity's Lack of Path Neutrality: Predicting Quantity Varying Whether Beginning Data Point Was an Original HIE Point**



**Source:** Congressional Research Service (CRS) analysis.

**Note:** Dashed line from **Figure 6**, based on moving from higher original HIE data points to consecutively lower ones. Solid line predicted using arc-elasticity formulas and based on  $(p_0, Q_0)$  points on the dashed line.

The biggest differences between the curves occur when price  $p_1$  is less than the 13% used for  $p_0$ . The smaller the coinsurance, the larger the difference. From a beginning point of (13%, 79%), the free-plan value is predicted at 111% of the actual

HIE free-plan value. Over the domain from 13% to 95%, the largest difference between the curves is two-tenths of one percentage point. Thus, even when the beginning data point is not one of the original points used to calculate the elasticity, applying the arc elasticity to predict HIE results yields relatively consistent results, except when predicting based on small coinsurance rates. In other words, even though arc elasticities are generally not path neutral, their application for HIE results produces curves that appear relatively path neutral, except at smaller coinsurance levels. Except when dealing with free-plan levels, arc elasticities appear useful in reasonably replicating HIE results.

## Induction Factors

**Table 4** displays the induction factors calculated according to Eq. (14) and based on the coinsurance ( $p_0$  and  $p_1$ ) and spending levels ( $Q_0$  and  $Q_1$ ) in **Table 1**. As previously mentioned, the value of an induction factor is the percentage of the difference in two plans' out-of-pocket payments that directly affects total health care spending. **Table 4** expresses these percentages as decimals (for example, 1.16 rather than 116%). As in **Table 2**, which shows the arc elasticities, the first three rows of **Table 4** show the factors when compared to the free plan. The next three display the factors between consecutive coinsurance rates. The last row shows the factors between 25% and 95% coinsurance. As previously discussed, induction factors are not reversible — their value depends on which of the two data points in the calculation is chosen as the starting point ( $p_0, Q_0$ ). As a result, for each pair of HIE coinsurance rates, there are two induction factors — one using the lower coinsurance as  $p_0$  and one using the higher coinsurance as  $p_0$ .

**Table 4. Induction Factors Between Average Coinsurance Amounts, By Type of Service**

Average coinsurance range	Lower coinsurance as starting point				Higher coinsurance as starting point			
	Outpatient	Inpatient	Total medical	Dental	Outpatient	Inpatient	Total medical	Dental
0% - 25%	1.16	1.16	1.16	0.84	1.63	1.63	1.63	1.06
0% - 50%	0.84	0.64	0.74	0.64	1.45	0.94	1.17	0.94
0% - 95%	0.54	0.42	0.47	0.53	1.10	0.70	0.86	1.05
0% - 25%	1.16	1.16	1.16	0.84	1.63	1.63	1.63	1.06
25% - 50%	0.73	0.17	0.45	0.56	0.90	0.18	0.51	0.65
50% - 95%	0.34	0.26	0.28	0.59	0.41	0.30	0.32	0.80
25% - 95%	0.44	0.22	0.32	0.52	0.64	0.26	0.42	0.83

**Source:** Congressional Research Service (CRS) calculations on data in **Table 1**, which is from Table 4.17, Joseph P. Newhouse et al., *Free for All? Lessons from the RAND Health Insurance Experiment* (Cambridge, Massachusetts: Harvard University Press, 1993).

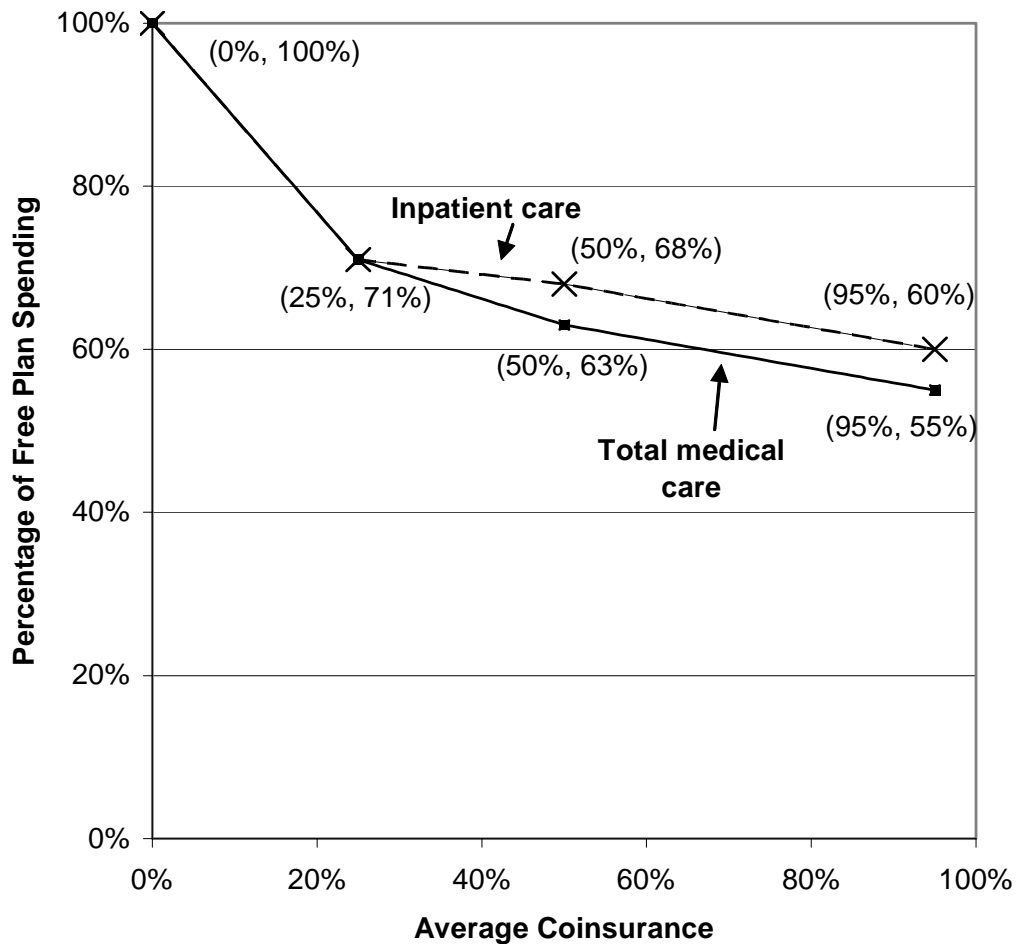
**Predicting Quantity with Induction Formulas.** Induction factors are path neutral (that is, they consistently predict quantity, using Eq. (13)) when the following conditions hold:

- the beginning point ( $p_0, Q_0$ ) is one of the original data points that was used in calculating the induction factor;

- the induction factor was calculated based on that  $(p_0, Q_0)$  as the starting point; and
- the price in the other original data point on which the induction factor was based  $(p_1, Q_1)$  has the same relationship to starting point  $(p_0, Q_0)$  as does the price being used to predict quantity (that is, the  $p_1$  used to calculate the induction factor and the price for which quantity is being predicted are both greater than or are both less than  $p_0$ ).

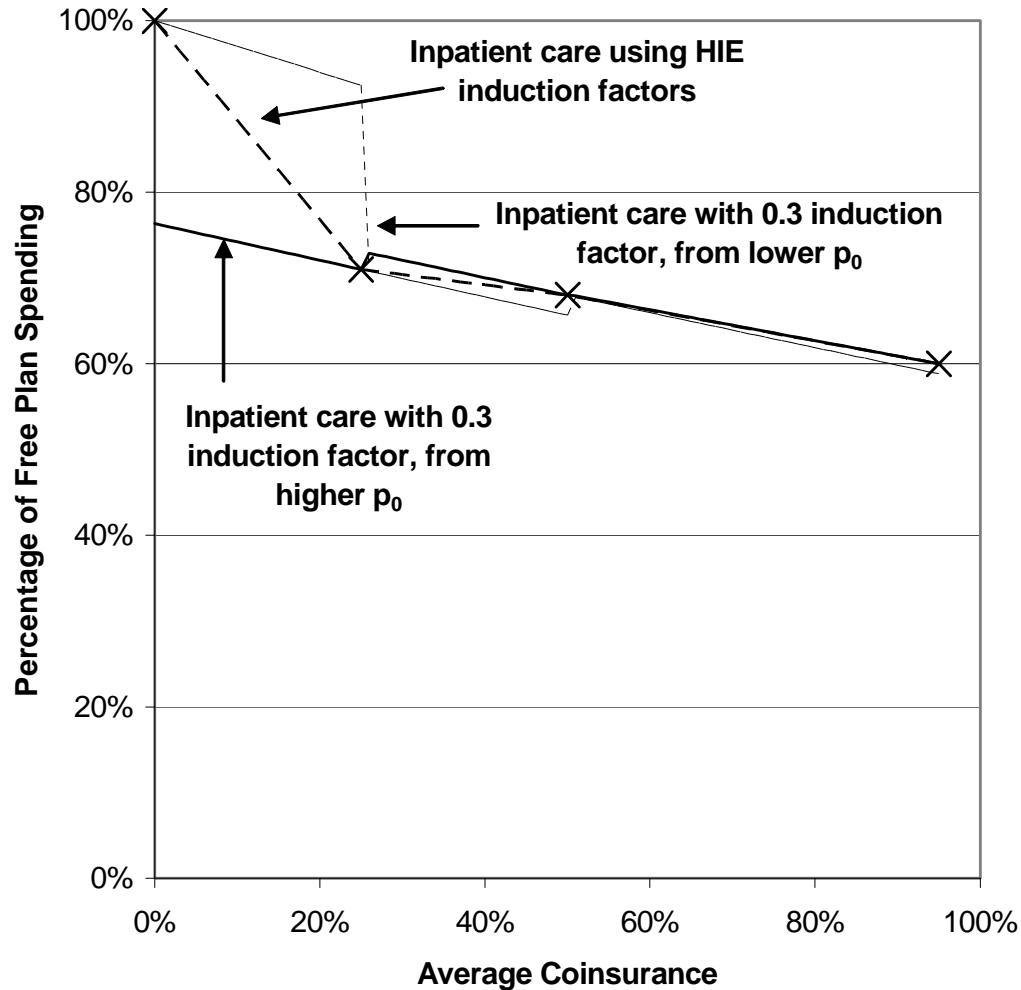
**Figure 8** shows the results when abiding by these conditions for total medical (solid line) and inpatient care (dashed line). They are simply line segments drawn between the original data points in **Table 1**.

**Figure 8. Predicting Quantity Using Induction Factors and Original Data Points from HIE**



**Source:** Congressional Research Service (CRS) analysis.

**Figure 9. Predicting Quantity of Inpatient Care, By Induction Factor and Beginning HIE Data Point**



**Source:** Congressional Research Service (CRS) analysis.

**Note:** The lines are predicted by applying the induction factors and the HIE price-quantity data points to the appropriate formula (Eq. (13)), where  $p_1$  is the average coinsurance along the x-axis and the percentage of free-plan spending is predicted by the formula and graphed against the y-axis.

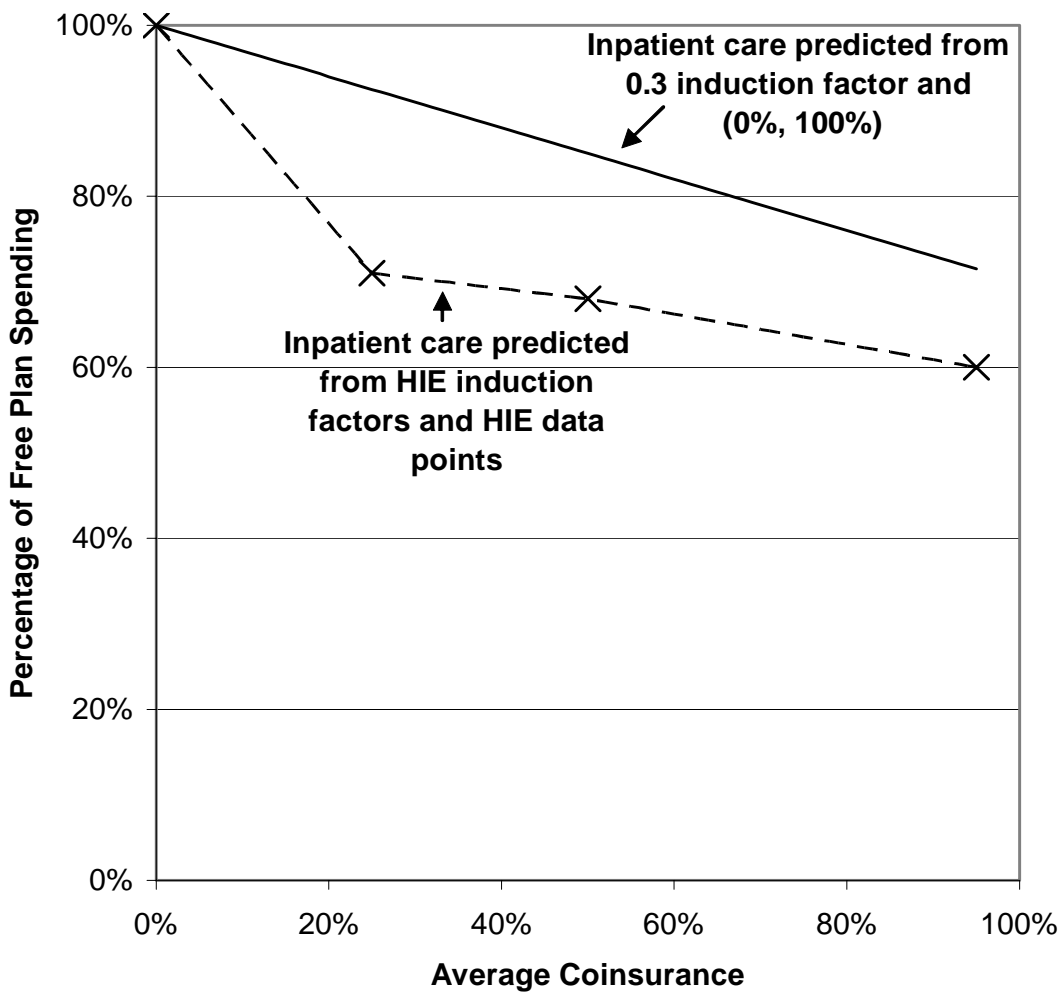
The induction factors in the CRS/Hay models, however, do not vary by coinsurance. For each type of care, the induction factors are held constant across the domain of coinsurance levels. The CRS/Hay models use the induction factors most commonly cited: 0.3 for inpatient hospitalization, 1.0 for prescription drugs, and 0.7 for all other medical care.<sup>23</sup> Using the original HIE data points as the starting points ( $p_0$ ,  $Q_0$ ), **Figure 9** shows the predicted quantity of inpatient care using a constant induction factor of 0.3. The thin line is predicted quantity based on the lower HIE

<sup>23</sup> See, for example, Table II-2A in Edwin Husted, et al., "Medical Savings Accounts: Cost Implications and Design Issues," American Academy of Actuaries' Public Policy Monograph No. 1, May 1995, at [[http://www.actuary.org/pdf/health/msa\\_cost.pdf](http://www.actuary.org/pdf/health/msa_cost.pdf)]. (Hereafter cited as Husted, et al., *Medical Savings Accounts: Cost Implications*.)

coinsurance between two points; the heavier solid line is based on the higher HIE coinsurance. The dashed line is the same as in **Figure 8**.

When using the 0.3 induction factor, the lines that result in **Figure 9** have relatively constant slopes (not counting the graph's vertical lines that link the line segments). Solving Eq. (21) for the slope and holding the induction factor  $I$  constant illustrates why the slope is relatively flat and constant. Based on the four original HIE data points (for  $Q_0$ ) and a constant induction factor of 0.3, the slope of the resulting two lines is between -0.18 and -0.30. This is consistent with the slope of the line segments between the HIE data points where the coinsurance is not zero. However, between the HIE data points of (0%, 100%) and (25%, 71%), the slope is -1.16. As a result, the two lines based on the 0.3 induction factor vary substantially from the line based on the HIE data points, although each of the two lines based on the 0.3 induction factor passes through one original HIE point — the one that served as  $(p_0, Q_0)$  in the formula for predicting quantity.

**Figure 10. Comparison of Results of Constant Induction Factor from Free-Plan Spending with Induction Factors and Original Data Points from HIE**



Source: Congressional Research Service (CRS) analysis.

There are two lines predicted from the original HIE points and the 0.3 induction factor because the use of a constant induction factor effectively assumes the factor is reversible. Of course, it is not reversible, as illustrated by the two lines that emerge between two data points when holding the induction factor constant.

The dissimilarity between the slopes of the lines based on the HIE factors versus the 0.3 factor causes particular concern for the CRS/Hay models, which produce results based on cost-sharing additions to a free plan. Along with the same dashed line in the previous two graphs based on the HIE data, **Figure 10** shows predicted inpatient care from a constant 0.3 induction factor and from the free-plan spending data point of (0%, 100%). Where average coinsurance is 25%, the difference between the two lines is greatest: The predicted quantity of inpatient care is 30% higher than the HIE results. These results suggest that, if induction factors are to be used, they should not be constant against the entire domain of cost-sharing.

## Cubic Formula

Both arc elasticities and induction factors have limitations when trying to apply them to replicate HIE results. These limitations are severe when doing analyses based on free-plan levels, as illustrated in **Figure 6**, or when using a constant factor for all levels of cost-sharing, as in **Figure 10**. This has huge implications for the CRS/Hay models because they are built on a base dataset that represents free-plan spending and uses constant factors regardless of cost-sharing. These findings suggest the need for another method to estimate the impact of cost-sharing on demand for health care.

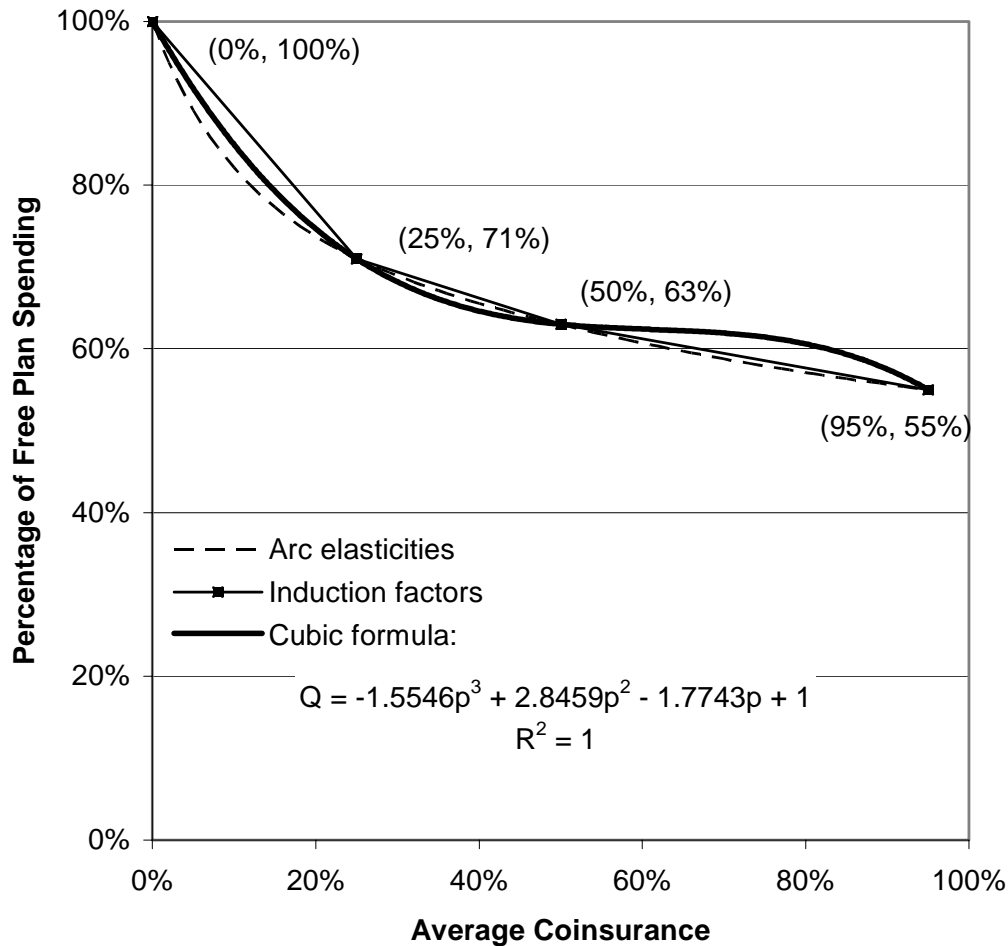
Some other method that yields better model results may lack otherwise desirable characteristics not critical in modeling. For example, an arc elasticity has applications for analyzing all kinds of goods and services. It produces a *standardized* value for comparing people's price sensitivity for all kinds of goods and services. Standardization is obtained by taking the slope of the line (or of the demand curve) and applying the original or average price and quantity combinations so that the units are no longer a part of the factor, as demonstrated in Eq. (19) and Eq. (20). For modeling purposes, however, such standardization is not only unnecessary but is also problematic in that it leads to the problems observed in **Figure 6**. A better method for replicating the HIE results may not ultimately produce factors that are standardized for comparing other goods and services. It is more important, however, that the method produce values that are reversible, path neutral and consistent with the HIE results.

The HIE results of interest for our modeling purposes are the four price-quantity data points, in terms of average coinsurance and percentage of free-plan spending: (0%, 100%), (25%, 71%), (50%, 63%), and (95%, 55%). With only four points, a cubic formula can be calculated using least squares fit, which will create a curve passing through all four HIE points. For the remainder of this report, this formula is referred to as "the cubic formula," where Q is the percentage of free-plan spending predicted from a particular average coinsurance, p:

$$(26) \quad Q = -1.5546p^3 + 2.8459p^2 - 1.7743p + 1$$

**Figure 11** shows the results of this formula as a heavy line, along with the ideal arc-elasticity and induction results presented earlier. The dashed line is based on the arc elasticities, and the lighter solid line is based on the induction factors. All three are for total medical care.

**Figure 11. Predicting Quantity Using Cubic Formula, Compared to Ideal Arc Elasticities and Induction Factors, From Original HIE Data Points**



**Source:** Congressional Research Service (CRS) analysis.

**Note:** The arc-elasticity curve is the same as the dashed line in **Figure 6**, which predicts quantity based on the higher of consecutive original HIE points as  $(p_0, Q_0)$  and using the unique arc elasticity between each pair of points, as shown in **Table 2**. The induction-factor curve is the same as the solid line in **Figure 8**, which predicts quantity based on the higher of consecutive original HIE points as  $(p_0, Q_0)$  and using the unique induction factor between each pair of points and for moving from higher to lower cost-sharing, as shown in **Table 4**. While these are the ideal scenarios for the arc-elasticity and induction-factor curves, the cubic formula always yields the same results, without needing a  $(p_0, Q_0)$  and regardless of whether one is moving from higher or lower cost-sharing.

The cubic formula has several improvements over the other methods. For example, because  $(p_0, Q_0)$  is not part of the formula (since the original HIE points are inherent in the cubic formula), path neutrality and reversibility are not concerns. The

quantity predicted based on a particular price will always be the same using the cubic formula. Moreover, calculating the slope (that is, change in quantity / change in price) at any point along the curve is quite simple, using the derivative of Q with respect to p:<sup>24</sup>

$$(27) \text{ slope of } Q \text{ at a given coinsurance } (p) = Q'(p) = -4.6638p^2 + 5.6918p - 1.7743$$

A potential concern one might note in **Figure 11** is the difference between the cubic formula and the other two curves between 50% and 95% coinsurance. Although the arc-elasticity and induction curves are close to one another in this domain, the cubic-formula curve appears much higher. The difference between the cubic-formula curve and the induction curve is 3.1%.<sup>25</sup> Between 0% and 50% coinsurance, the cubic-formula curve is *lower* than the induction-factor line segments so that, overall, the area under both curves is nearly identical — 64.6% and 64.7% respectively.<sup>26</sup> The area under the arc-elasticity curves is 63.3%, approximately 2% less than the area under the other two curves.<sup>27</sup> Because the HIE data provided only four data points, it is not known which of the three curves best reflects the impact of cost-sharing between those points. Considering this as well as the relatively small overall differences between the curves, the shape of the curves should not be an overriding criterion in determining which method to use.

## Estimating Free-Plan Spending

As presented here, each of the methods take a particular average coinsurance to predict the percentage of free-plan spending associated with that coinsurance. This section discusses how these results would be applied to create free-plan spending levels, such as those used in the CRS/Hay models, and how their results vary.

The example case is a person who was enrolled in a high-deductible health plan. The deductible was \$1,000, after which a 25% coinsurance applied. During the year, the person had total medical expenses of \$1,500.<sup>28</sup> Of this total, the person paid \$1,125, or 75%. If this person had been in a free plan, her spending would likely have been more than \$1,500.

<sup>24</sup> The slope of the demand curve would be the reciprocal of Eq. (27).

<sup>25</sup> This is determined by calculating the percentage difference in the integral of Eq. (26) and the area under the straight line created by the ideal induction-factor results:  
 $1 - \int (-1.5546p^3 + 2.8459p^2 - 1.7743p + 1) dp / [(95\% - 45\%)(55\% + \frac{1}{2}(63\% - 55\%))]$   
 where p ranges from 50% to 95%.

<sup>26</sup> These numbers were calculated as in Footnote 24, using the integral of Eq. (26) for the cubic formula and the area under the straight lines for the induction factors.

<sup>27</sup> The area under the arc-elasticity curves was obtained by integrating Eq. (7) between consecutive pairs of HIE points, using the higher coinsurance of each pair as  $p_0$ :  
 $\int Q_0(Ep_0 - Ep_1 - p_1 - p_0) / (Ep_1 - Ep_0 - p_1 - p_0) dp_1$   
 where E,  $Q_0$  and  $p_0$  are constants based on the HIE data, over the domain between the two HIE data points.

<sup>28</sup> The assumption for all of these examples is that all expenses are covered medical expenses.



To calculate free-plan spending using the arc-elasticity formulas, the appropriate elasticity for total medical spending is needed from **Table 2**. Because the intent is to predict free-plan spending (that is,  $p_1=0$ ), one of the values in the calculation should be based on a coinsurance of zero, as in the first three rows of **Table 2**. The other value relevant for choosing the appropriate elasticity is the other coinsurance of 75%. In the table, the nearest coinsurance rates to 75% are 50% (with an elasticity of -0.23) and 95% (with an elasticity of -0.29). Based on its distance between 50% and 95% coinsurance, the 75% coinsurance is estimated through simple imputation to have an elasticity of -0.26333.<sup>29</sup> The  $(p_0, Q_0)$  to be applied in Eq. (7) is the (75%, \$1,500) given in the example, predicting free-plan spending as follows:

$$\begin{aligned}
 (28) \quad Q_1 &= Q_0(E_{p_0} - E_{p_1} - p_1 - p_0) / (E_{p_1} - E_{p_0} - p_1 - p_0), \text{ where } p_1=0 \\
 &= Q_0(E_{p_0} - p_0) / (-E_{p_0} - p_0) \\
 &= \frac{1 - E}{1 + E}, \text{ where } E = -0.26333 \\
 &= \$1,500 (1+0.26333) / (1-0.26333) \\
 &= \$2,572
 \end{aligned}$$

As shown in Eq. (28), predicting free-plan spending — that is, predicting  $Q_1$  where  $p_1=0$  — causes  $p_0$  to cancel out of the formula. Thus, the elasticity is the only variable remaining that reflects the original plan's 75% coinsurance. As a result, when dealing with free-plan information, constant results can be avoided only by calculating precise elasticity values. The results are quite sensitive to the value of the elasticity. An arc elasticity of -0.23 would have yielded free-plan spending of \$2,396. An arc elasticity of -0.29 would have yielded free-plan spending of \$2,725.

When dealing with a free plan, the use of a continuous arc elasticities is required to predict spending that is not constant over a given domain. In other words, the arc elasticity must be used to create unique elasticities at each given point, like a point elasticity. Obviously, this is not the role of the arc elasticity. The approach applied in Eq. (28) to work around the factor's limitation when dealing with a free plan is arguably a misuse of its factors. Thus, when applying arc elasticities to free-plan information, an analyst must choose between possibly misusing the factors or predicting constant spending regardless of cost-sharing. Neither is desirable.

In applying the induction-factor formulas, not only should the factor be chosen from the first three rows of **Table 4** but should also be taken from the penultimate column, for "higher coinsurance as starting point." This matters because induction factors are not reversible. As with the elasticities, there are two induction factors to choose between — 1.17 (based on coinsurance from 0% to 50%) or 0.86 (based on coinsurance from 0% to 95%). These constant factors would predict unique amounts of spending for every coinsurance in the domain, unlike elasticities. As a result,

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<sup>29</sup> Calculated as  $-0.23 - [(75\% - 50\%) / (95\% - 50\%) * (0.29 - 0.23)]$ . Also, **Figure 7** showed little difference in the results when the starting point for predicting quantity was not one of the original HIE points. However, those results were calculated between consecutive HIE points with the corresponding elasticity. In this example, there is greater variation due to the larger coinsurance domain used.

calculating an induction factor for a given coinsurance is not as crucial, but doing so produces continuous factors that seem more accurate than the factors at 50% and 95%. Based on its distance between 50% and 95% coinsurance, the 75% coinsurance is estimated to have an induction factor of 0.9978. The free-plan spending level is then calculated using both Eq. (11) and Eq. (13) respectively below:

$$\begin{aligned}
 (29) \\
 Q_1 &= Q_0 + I(OOP_0 - OOP_{1*}) \\
 &= \$1,500 + 0.9978(\$1,125 - \$0) \\
 &= \$2,623
 \end{aligned}$$

$$\begin{aligned}
 (30) \\
 Q_1 &= Q_0(1 + I(p_0 - p_1)) \\
 &= \$1,500(1 + 0.9978(75\% - 0\%)) \\
 &= \$2,623
 \end{aligned}$$

This is 2% higher than the comparable arc-elasticity amount. These results are also sensitive to the value of the factor. An induction factor of 0.86 would have yielded free-plan spending of \$2,468. An induction factor of 1.17 would have yielded free-plan spending of \$2,816.

Applying the cubic formula to the same example is more straightforward in that there are no factors to decide among. Thus, the free-plan spending level is calculated by applying the price of 75% coinsurance as follows:

$$\begin{aligned}
 (31) \\
 Q &= -1.5546p^3 + 2.8459p^2 - 1.7743p + 1 \\
 &= -1.5546(75\%)^3 + 2.8459(75\%)^2 - 1.7743(75\%) + 1 \\
 &= 61.4\%
 \end{aligned}$$

In other words, the cubic formula estimates that an average coinsurance of 75% yields a quantity that is 61.4% of free-plan spending. Thus, the \$1,500 in total spending is 61.4% of free-plan spending, and this free-plan spending results:

$$\begin{aligned}
 (32) \\
 \$1,500 / 61.4\% &= \$2,442
 \end{aligned}$$

Although there is a range of possible results from the other two methods, the cubic formula produces a single result. That result is 5% lower than the arc-elasticity result in Eq. (28) and 7% lower than the induction-factor result in Eq. (30).

## Predicting Spending From Estimated Free-Plan Spending

**Pure Coinsurance Plan.** Based on the free-plan spending estimates above, one can predict spending in a plan with nominal coinsurance of 75% and no deductible or out-of-pocket maximum. In this case, of course, the nominal coinsurance also serves as the average coinsurance. A priori, one might expect total spending to be predicted at \$1,500 because the average coinsurance of 75%, as before. Once more, the arc elasticity of -0.26333 is used in Eq. (7), with  $p_0=0\%$ ,  $Q_0=\$2,572$  and  $p_1=75\%$ :

$$\begin{aligned}
 (33) \quad Q_1 &= Q_0(E_{p_0} - E_{p_1} - p_1 - p_0) / (E_{p_1} - E_{p_0} - p_1 - p_0), \text{ where } p_0=0 \\
 &= Q_0 (- E_{p_1} - p_1) / (E_{p_1} - p_1), \text{ where } p_1 \text{ cancels out} \\
 &= Q_0 (1+E) / (1-E) \\
 &= \$2,572 (1 - 0.26333) / (1 + 0.26333) \\
 &= \$1,500
 \end{aligned}$$

As illustrated in **Figure 6**, using constant arc elasticities to predict spending from free-plan values (that is,  $p_0=0$ ) also yields a constant value. The arc-elasticity formula causes spending to be predicted based solely on the value of the elasticity, with its impact on the free-plan spending of \$2,572. Calculating continuous elasticities is not only problematic, as was mentioned before, but it is also complicated, requiring one to add a methodology to a methodology.<sup>30</sup>

Predicting spending from the estimated free-plan level using the induction factors requires choosing a different induction factor than was used in estimating the free-plan value, even though the analysis is of the same coinsurance amounts. A new factor must be chosen because induction factors are not reversible and, in this case, the analysis is of moving from no cost-sharing to substantial cost-sharing of 75% rather than vice versa. The applicable induction factors from **Table 4** are 0.47 and 0.74. For this example, the induction factor is calculated as 0.59 and is applied in Eq. (13) as follows, with  $p_0=0\%$ ,  $Q_0=\$2,623$ , and  $p_1=75\%$ :

$$\begin{aligned}
 (34) \quad Q_1 &= Q_0 (1 + I(p_0 - p_1)) \\
 &= \$2,623 (1 + 0.59(0\% - 75\%)) \\
 &= \$1,462
 \end{aligned}$$

This result is approximately 2.5% less than the \$1,500 total spending that should have been produced, in spite of the precise calculation of the induction factor. The difference is due to induction factors' lack of path neutrality and the issues surrounding the calculation of the induction factor itself. An induction factor of 0.571 would have predicted quantity of \$1,500.

The cubic formula produces the percentage of free-plan spending from the coinsurance. Eq. (31) already predicted that a 75% coinsurance yields quantity that is 61.4% of free-plan spending. Since this led to a free-plan value of \$2,442 (shown in Eq. (32)), the predicted spending in a 75% coinsurance plan would be calculated as  $\$2,442 * 61.4\% = \$1,500$ . This is not surprising considering that the \$2,442 was calculated as  $\$1,500 / 61.4\%$ , so \$1,500 emerges by necessity when multiplying it by 61.4%. This demonstrates the cubic formula's path neutrality.

**Typical Plan Structure.** Pure coinsurance plans are virtually nonexistent. Today's health insurance plans have not only coinsurance but copayments, deductibles and out-of-pocket maximums. This example illustrates how the

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<sup>30</sup> There is an interesting byproduct of the price levels falling out of the arc-elasticity formula when dealing with a free plan. The arc elasticities become path neutral, as demonstrated in this example by the predicted spending of \$1,500 emerging by identity.

estimated free-plan spending can be used to predict spending for the same person in a plan with a deductible of \$500 followed by coinsurance of 62.5%, with an out-of-pocket maximum of \$2,000. Although not a pure coinsurance plan, this plan would also have 75% average coinsurance at \$1,500 total spending. Thus, assuming average coinsurance is an accurate predictor of total spending, one might expect the methods to predict \$1,500 of total spending from the free-plan level for this person.

In this instance, \$1,500 may be the desired total spending under the new plan. However, the only information that would be known in the CRS/Hay models is the free-plan spending for this person. Because applying the elasticities to predict spending requires an average coinsurance, the only information for calculating this is the free-plan spending level of \$2,572. In other words, calculating the average coinsurance of a plan that does not have pure coinsurance requires using the given spending level as the basis. In this example, the first step would be to calculate out-of-pocket spending under the new plan given total spending of \$2,572. This is the same calculation that would be done for the induction-factor formula, as follows:

$$(35) \\ OOP_{1*} = 500 + 62.5\% (2,572 - 500) = 1,795$$

The average coinsurance based on free-plan spending ( $Q_0$ ) would then be as follows, requiring the introduction of a new variable ( $p_{1*}$ ):

$$(36) \\ p_{1*} = OOP_{1*} / Q_0 = 1,795 / 2,572 = 69.8\%$$

The actual average coinsurance will likely be different once quantity is adjusted downward because of the cost-sharing. Nevertheless, in lieu of any other known number, one must then decide which elasticity to use based on **Table 2**. Again, because calculating the elasticity is critical when dealing with a free plan, a precise elasticity is used, -0.25639, based on the average coinsurance. This produces total spending of \$1,523, approximately 1.5% higher than \$1,500:

$$(37) \\ Q_1 = Q_0(Ep_0 - Ep_{1*} - p_{1*} - p_0) / (Ep_{1*} - Ep_0 - p_{1*} - p_0), \text{ where } p_0=0 \\ = Q_0 (1+E) / (1-E) \\ = \$2,572 (1 - 0.25639) / (1 + 0.25639) \\ = \$1,523$$

Using induction factors to predict spending is relatively straightforward using Eq. (11), since it uses  $OOP_{1*}$ , although its value differs from the one calculated in Eq. (35) because the free-plan spending estimated from the induction factors in Eq. (29) is different than the free-plan spending based on the elasticities, as shown in Eq. (28). The induction factor's free-plan spending of \$2,623 for this person produces the following:

$$(38) \\ Q_1 = Q_0 + I (OOP_0 - OOP_{1*}) \\ = \$2,623 + I (\$0 - \$1,827)$$

The challenge is deciding the value of the induction factor, I. Again, the average coinsurance will likely be different once quantity is adjusted downward because of the cost-sharing, but in lieu of any other known number, one must use  $p_{1*}$  to choose an induction factor based on **Table 4**. (The CRS/Hay models, and most other models using induction factors for modeling purposes, use constant induction factors regardless of cost-sharing level, already shown to be problematic.) The average coinsurance ( $p_{1*}$ ) based on the free-plan spending in the new plan would be approximately 69.6%. Based on where 69.6% falls between 50% and 95% coinsurance, the induction factor is estimated at 0.6221. Plugging this value into Eq. (38) then yields \$1,486, which is 1% smaller than the \$1,500 expected a priori.

Alternatively, predicting quantity by directly applying the 69.6% average coinsurance in the induction-factor formula (based on Eq. (13)) based on free-plan spending also yields \$1,486:

$$\begin{aligned} (39) \\ Q_1 &= Q_0 (1 + I(p_0 - p_{1*})), \text{ where } p_{1*} = OOP_{1*}/Q_0 \\ &= \$2,623 (1 + 0.6221(0\% - 69.6\%)) \\ &= \$1,486 \end{aligned}$$

This should not be surprising, since setting the first line in Eq. (38) equal to the first line in Eq. (39) yields an identity:

$$\begin{aligned} (40) \\ Q_0 + I(OOP_0 - OOP_{1*}) &= Q_0 (1 + I(p_0 - p_{1*})), \text{ where } p_0 = OOP_0/Q_0 \text{ and } p_{1*} = OOP_{1*}/Q_0 \\ Q_0 + I(OOP_0 - OOP_{1*}) &= Q_0 (1 + I(OOP_0/Q_0 - OOP_{1*}/Q_0)) \\ Q_0 + I(OOP_0 - OOP_{1*}) &= Q_0 + I(OOP_0 - OOP_{1*}) \end{aligned}$$

Thus, when using induction factors, the average coinsurance derived from applying a plan structure to a given price-quantity combination yields the same results as using the nominal out-of-pocket dollar amounts. One of the most common arguments for using induction factors is that it enables one to handle complex plan designs by virtue of the nominal out-of-pocket amounts. In actuality, its methodology is no different than using the average coinsurance. As a result, the limitations of the arc elasticity from calculating the average coinsurance in a typical plan structure are the same limitations faced by the induction-factor formulas. This point is typically obscured, however, because the induction factors rely on the nominal dollar amounts.

As with arc elasticities and induction factors, the cubic formula also relies on the average coinsurance of the new plan calculated from the spending levels of the old plan ( $Q_0$ ). Applying the cubic formula's average coinsurance of approximately 70.2%, based on its free-plan spending level, produces the following:

$$\begin{aligned} (41) \\ Q &= -1.5546p^3 + 2.8459p^2 - 1.7743p + 1, \text{ where } p=70.2\% \\ &= 61.9\% \end{aligned}$$

Applying this percentage-of-free-plan spending to the free-plan spending of \$2,442 (from Eq. (32)) yields \$1,512, not quite 1% higher than \$1,500.

Using the same approaches to predict spending in the original plan, which had a \$1,000 deductible and 25% coinsurance, based on the free-plan spending levels shown in Eqs. (28-32) yields the values shown in **Table 5**. The target amount is \$1,500. Once again, the cubic formula produces results closest to the target amount. To re-emphasize the point, the induction-formula results were calculated using the first line of both Eq. (38) and Eq. (39). As expected, the results were identical.

Although induction factors are not reversible, this added complication was previously justified by the factors' capacity to predict spending based on a new plan's cost-sharing structure as applied to the original plan's spending. The arc-elasticity and cubic formulas work best when the new plan is only pure coinsurance. Any other plan structure forces one to resort to calculating an average coinsurance based on the original plan's spending level, which introduces some error. However, it was shown above that the induction factor's methodology is no different than using the average coinsurance calculated from the original plan's spending level, introducing the same kind of error. This seems to nullify the case for tolerating the induction factors' lack of reversibility and the concomitant complexity. Moreover, the induction-factor methodology is the only one of the three that does not replicate a plan's original spending level when modeling a pure-coinsurance plan, as shown in Eq. (34). This is because the induction-factor results are based on  $p_{1*}$  even when  $p_1$  is known.

**Table 5. Predicted Spending of Example Person in Plan With \$1,000 Deductible and 25% Coinsurance, Based on Predicted Free-Plan Spending, By Cost-Sharing Method**

	Arc elasticity	Induction factor	Cubic formula	Target amount
Average coinsurance ( $p_{1*}$ )	54.2%	53.6%	55.7%	
Value of factor	-0.23554	0.7184	Not applicable	
Predicted spending ( $Q_1$ )	\$1,592	\$1,613	\$1,529	\$1,500
Difference from target amount	6.1%	7.5%	1.9%	

**Source:** Congressional Research Service (CRS) calculations.

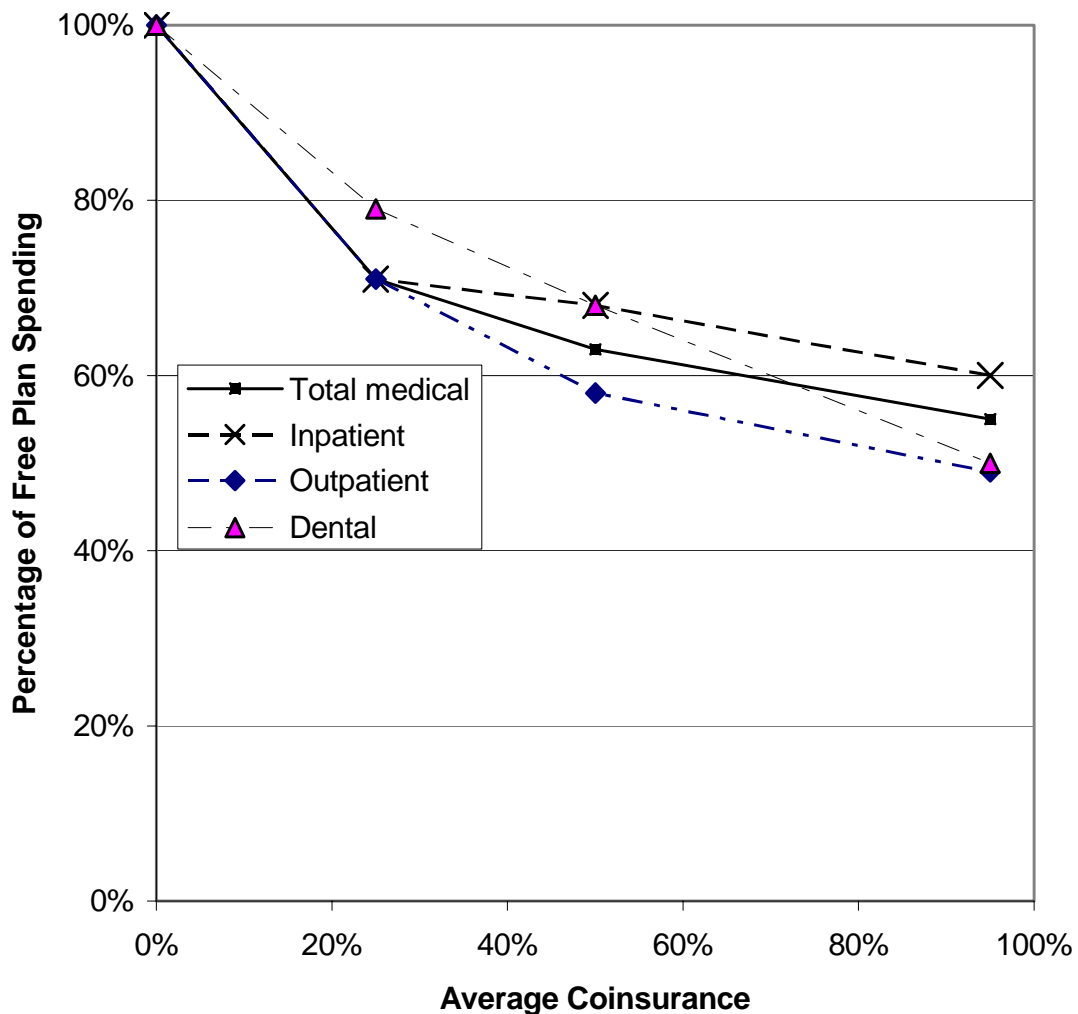
**Notes:** Average coinsurance is based on applying the plan design to the predicted free-plan spending for each factor, shown in Eqs. (28-32). The "value of factor" for the arc elasticity and induction factor is calculated from the values in **Table 2** and **Table 4**, based on the location of the average coinsurance between 50% and 95% coinsurance. The cubic formula requires no factor. "Predicted spending" is based on the calculated "value of factor." If the given values from **Table 2** and **Table 4** were used instead of the calculated values, the "difference from target amount" would be -5.6% or 7.4% for elasticities and, for induction factors, 5.5% or 30.8%. All exceed the cubic formula's difference.

The quantity predicted by the cubic formula was closer to the desired amount than the quantity predicted by the other methods. This is even after taking extreme care to calculate seemingly the best possible values for the induction factors and arc elasticities. If such care is not taken (that is, if constant factors are used across cost-sharing levels), then the cubic formula would certainly produce results more consistent with the HIE. Not having to calculate values for a factor makes the cubic formula preferable from a practical standpoint as well.

## Predicting Spending by Type of Care

Most of the preceding discussion has focused on how the methodologies can be used to predict *total* medical care spending. One might expect, however, that the effect of cost-sharing will vary depending on the type of service — whether inpatient or outpatient, for example. One of the most interesting HIE results is that spending in the 25% plan averaged 71% of free-plan spending for *both* outpatient and inpatient care, as shown in **Table 1** and illustrated in **Figure 12**. Because of this concordance, the corresponding arc elasticities (**Table 2**) and induction factors (**Table 4**) do not vary by type of care between 0% and 25% coinsurance. Between 25% and 95% coinsurance, spending does differ by type of care, as do the factors.

**Figure 12. Effect of Average Coinsurance on Spending, by Type of Service**



**Source:** Table 4.17, Joseph P. Newhouse et al., *Free for All? Lessons from the RAND Health Insurance Experiment* (Cambridge, Massachusetts: Harvard University Press, 1993).

**Note:** “Total medical” excludes dental.

**Constant Induction Factors.** Although the CRS/Hay models do not vary the induction factors by cost-sharing levels, the factors do vary by type of service: 0.3 for inpatient hospitalization, 1.0 for prescription drugs, and 0.7 for all other care.<sup>31</sup> As was illustrated in **Figure 10**, these values predict spending levels that do not always line up well with the HIE. It is arguable that medical care has changed so that the constant factors are more in line with current utilization patterns than the HIE results. However, that is not the argument made. These constant factors “were based largely on the RAND study.”<sup>32</sup> It is difficult to determine how these constant factors were obtained from the range of HIE-based induction factors in **Table 4**.

A decade ago, a team of actuaries reexamined these constant factors, since “the management, delivery, and mix of health care services have changed dramatically since the study was performed.” Some of the workgroup members thought the factors should be higher, while others thought they should be lower. Ultimately they decided to leave the constants unchanged but noted that “(o)ne set of factors is not appropriate for all uses. The factors used should be carefully considered in the context of the specific situation.”<sup>33</sup> The induction factors currently used in the CRS/Hay models still have these values.

**Inpatient and Outpatient Care.** For practical modeling purposes, one must consider whether the differences in the HIE results by type of care would substantially affect model results. If not, it is probably not worth varying the factors by type of care. Again, between 0% and 25% coinsurance, there is no difference between inpatient and outpatient care whatsoever, in terms of percent of free-plan spending. The largest difference is at 95% coinsurance. Differences at the 95% coinsurance are compared in this section.

From the example person above, a 95% pure-coinsurance plan predicted from free-plan levels would produce total medical spending shown in the gray column of numbers in **Table 6**. The table also shows what spending would be predicted if *all* spending had been either outpatient or inpatient care, and varying the factors accordingly. The table also shows the results for dental care.

**Table 6. Example Person’s Predicted Spending at 95% Coinsurance, by Type of Service and Factor**

Factor	Outpatient	Inpatient	Total medical	Dental
Elasticity	\$1,267	\$1,543	\$1,416	\$1,296
Induction	\$1,277	\$1,576	\$1,452	\$1,302
Cubic formula	\$1,196	\$1,465	\$1,343	\$1,221

**Source:** Congressional Research Service (CRS) calculations.

**Note:** “Total medical” excludes dental.

<sup>31</sup> These factors are used to calculate a weighted induction factor for each person in the models, based on their health care utilization by type of care.

<sup>32</sup> Husted, et al., *Medical Savings Accounts: Cost Implications*, p. 4.

<sup>33</sup> *Ibid.*



Although this section focuses on variation by type of service, the differences in the total medical column merit some discussion, even if it is somewhat repetitive. First, these amounts are based on the predicted free-plan values, which were based on the total spending of \$1,500 in the original plan with an average coinsurance of 75%. The three approaches produced different free-plan values. Applying the factors to the estimated free-plan spending to a 95% coinsurance should yield total medical spending that is 55.0% of the free-plan spending. This was so for the elasticity and cubic formulas; for the induction formula, it was 55.4%. Thus, the bulk of the difference among the factors was due to the difference in creating the free-plan values. As mentioned in that section, the results from the arc elasticities and the induction factors vary widely depending on the values chosen for the factors. Moreover, as illustrated in **Figure 11**, the methods' functions yield dissimilar results between the HIE coinsurance levels, and which one is superior is not known.

The cubic formula does not require the calculation of factors when predicting quantity. Because it does not have factors of its own, predicting spending by various types of care requires estimating new formulas. For each type of care, a different cubic formula must be estimated to be consistent with the HIE results. This is one practical limitation compared to elasticities and induction, which use the same formulas but different factors for different types of care. For inpatient care, the formula is estimated as  $Q = -2.2764p^3 + 3.7873p^2 - 1.9645p + 1$ . For outpatient care, it is  $Q = -0.8662p^3 + 1.9296p^2 - 1.5883p + 1$ . For dental care, it is  $Q = -0.782p^3 + 1.3865p^2 - 1.1377p + 1$ . For inpatient care in particular, the resulting curve is not ideal. Between 41.4% and 69.6%, the slope of the curve is actually positive.<sup>34</sup> While the HIE results are not known between the four original data points, it is counterintuitive that higher levels of cost-sharing would lead to *higher* inpatient spending. In spite of its other advantages, the cubic formula is problematic for producing spending levels by type of service, at least for inpatient care. The results in **Table 6** are not affected, however, because the coinsurance is 95%, one of the original HIE data points, which is replicated by the cubic formulas.

If the example person's spending were all inpatient, each of the three approaches would predict total spending that is 22%-23% higher than if it were all outpatient. Though large, this difference does not by itself merit accommodating type-of-service factors. First, this difference occurs at the 95% coinsurance level, an unusual amount of cost-sharing for a plan. When calculating average coinsurance on individual records, many may be at this coinsurance level, or even 100% if they are still in the plan's deductible range. Of course, in the deductible range, dollar amounts are relatively small. This leads to the second point that, in the aggregate, the differences resulting from using separate factors by type of care may largely offset. For example, the total medical spending amounts are based on the HIE data in which outpatient care made up 46% of the total and inpatient care made up 54%. Applying those percentages to the numbers for outpatient and inpatient in **Table 6** yields \$1,416 in total medical for the elasticities, \$1,439 for the induction factors, and \$1,342 for the cubic formulas. Only the calculated results using the induction factors vary from the predicted total medical amount in **Table 6** by more than a dollar. Thus, as long as

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<sup>34</sup> These coinsurance points were calculated by taking the derivative of the equation and solving it for  $Q'(p)=0$ .

one is predicting total spending, rather than by type of care, it is arguable that the total medical factors produce adequate results.

**Example Using Actual Data.** The preceding hypothesis was tested informally by using person-level expenditure data from the 2002 Medical Expenditure Panel Survey (MEPS) for those under age 65 with any health care spending. These results are shown in **Table 7**.

**Table 7. Average Predicted Spending, by Plan and Factor, Based on 2002 MEPS**

Plan	Cubic formula	Elasticity	Induction factor
Free plan (total medical values)	\$2,186	\$2,764	\$2,161
95% coinsurance (total medical values)	\$1,202	\$1,520	\$1,196
95% coinsurance (inpatient/outpatient values)	\$1,161	\$1,473	\$1,145
95% coinsurance (traditional induction values)	Not applicable	Not applicable	\$1,031

**Source:** Congressional Research Service (CRS) calculations on 2002 Medical Expenditure Panel Survey (MEPS).

**Note:** Among persons under age 65 with health care spending. The “traditional induction values” are 0.7 for outpatient care and 0.3 for inpatient care.

Using the total-medical cubic formula, free-plan values were calculated, producing an average of \$2,186. Based on those estimates, total medical spending was predicted to average \$1,202 in a 95% coinsurance plan, or 55% of the free-plan average.<sup>35</sup> Separately predicting outpatient and inpatient care, using the respective cubic formulas, yields total plan spending of \$1,161, a difference of 3.5% from the total-medical cubic formula result. This result emerges by outpatient spending being 49% of the free-plan level and inpatient spending being 60% of the free-plan level, replicating the result in **Table 1**. The total-medical result of \$1,202 differs from \$1,161 to the extent that the ratio of outpatient-to-inpatient spending in MEPS differed from that in the HIE.

These results will also vary depending on which services are included in each respective category. For example, if prescription drugs were not modeled separately but were lumped into outpatient care, which is a reasonable decision, the difference in predicted total spending would be 5.7%, depending on whether type-of-service formulas were used instead of the total medical formula.<sup>36</sup>

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<sup>35</sup> For this analysis, “total medical” consists of inpatient care (inpatient hospital stays, including zero-night stays and separately billing doctor expenses) and outpatient care (office-based, outpatient-hospital and emergency-room visits).

<sup>36</sup> It is not clear whether or not the HIE outpatient results included prescription drugs. The separate effect of cost-sharing on prescription drugs is discussed separately, which would suggest they were not included in outpatient care. The next section of this report discusses those results separately as well, so prescription drugs are left out of outpatient care here.

As was previously mentioned, when applying elasticities with a free plan, one must decide whether to misuse the factors, calculating quasi-point elasticities, or whether to use the constant elasticity values and thus predict constant spending across a broad domain of cost-sharing. For this example (and for simplicity's sake), the constant elasticities in **Table 2** will be used to predict free-plan values based on the MEPS data.

To create the free-plan values, the three elasticities from the gray column of the first three rows in **Table 2** were used. All records in the MEPS data with an average coinsurance between 0% and 25% had their total expenditures increased by 41% to create the free-plan spending level.<sup>37</sup> This was the case whether the person's average coinsurance was 0%, 25% or anything in between, which is a flaw in the arc elasticity when dealing with free-plan information. For coinsurance above 25% to 50%, the increase to the estimated free-plan spending was 60%. For coinsurance above 50%, the free-plan adjustment was 82%. This led to average free-plan spending estimated at \$2,764, 26% higher than the free-plan level predicted by the cubic formula.

Beginning with the free-plan spending estimated using the elasticity formula, flawed as it is, predicting total spending in the 95% coinsurance plan is less problematic. Even though a constant adjustment emerges, this is acceptable since the elasticity on which that adjustment is based relies on the same coinsurance levels (0% and 95%) used to create the elasticities from the HIE. As with the cubic formula, the elasticity in this case will predict 55% of the free-plan value using the total-medical elasticity. The outpatient and inpatient elasticities will yield 49% and 60% of free-plan spending for those services, respectively. Based on the free-plan estimates, the total-medical elasticity for a 95% coinsurance plan predicts average spending of \$1,520. At the same coinsurance level, applying the outpatient and inpatient elasticities to those types of care separately produces an average value of \$1,473. The arc elasticities' estimate of the 95% coinsurance vary by 3% depending on whether the type-of-service elasticities are used versus the total-medical elasticity. Of course, these results still differ dramatically from the cubic formula's largely because of the flawed nature of the arc elasticity's formula for creating free-plan values. Predicting total spending *from* free-plan spending is also problematic except when the coinsurance is at one of the HIE levels, which is the case here.

As with elasticities, continuous induction factors can be calculated over a range of coinsurance levels in an attempt to improve precision, though its impact on accuracy may be questionable. In applying induction factors to the MEPS data, the factors given in **Table 4** are used, turning to the next induction factor once the upper coinsurance level of the pairs is exceeded. For example, to create free-plan levels using the total-medical induction factors, 1.63 is used for coinsurance between 0% and 25%. For coinsurance above 25% to 50%, 1.17 is used. For coinsurance above 50%, 0.86 is used. This led to average free-plan spending estimated at \$2,161, about 1% lower than the free-plan level predicted by the cubic formula and substantially lower than that predicted by the arc elasticity.

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<sup>37</sup>  $(1-E)/(1+E) = (1+0.17)/(1-0.17)=1.41$ .

Although the arc-elasticity and cubic formula replicate 55.0% of free-plan spending at 95% coinsurance, the induction-factor results are slightly different for total medical, at 55.4%. Thus, spending in the 95% coinsurance plan using the 0.47 induction factor averages \$1,196. Calculating spending using the inpatient and outpatient factors (0.42 and 0.54 respectively) instead yields an average of \$1,145, a difference of more than 4%. Had an inpatient induction factor of 0.3 and an outpatient induction factor of 0.7 been used, spending would have averaged \$1,031 in the 95% coinsurance plan, illustrating once again that the induction factors of 0.7 for outpatient care and 0.3 for inpatient care do not replicate HIE results consistently.

Based on the MEPS data, average spending in a 95% coinsurance plan varies by 3% to 4%, depending on whether the total-medical or type-of-service formulas and factors are used. However, these differences are also affected by what is classified as outpatient versus inpatient care. It is important to note that this is the coinsurance level where the difference by type of service would be greatest. Since most plans would likely be at lower levels of coinsurance, where there is little or no difference by inpatient versus outpatient care according to the HIE results, individual analysts must decide whether such a type-of-service analysis is merited.

**Prescription Drugs.** Prescription drugs are a component of health care spending that has received increasing attention from those who follow health insurance issues. This is not surprising considering the growing proportion of health care spending that it comprises. In 1980, around the time of the HIE, prescription drugs made up 6% of health care spending. By 2003, that percentage had doubled, to 12%.<sup>38</sup> Not much attention was given to prescription drugs in the original HIE results, but a reexamination of the available information is merited in light of prescription drugs' growing prominence as a feature of health care coverage. One caveat of this analysis is that because of the changes over the past 25 years — that is, the increasing number, variety, price and utilization of prescription drugs — the HIE results regarding prescription drugs may be particularly out of date and inapplicable. Considering the popular notion that demand for prescription drugs is most elastic among health care goods and services, the section examines whether the HIE results affirm that notion and, to the extent the difference is measurable, whether it should be accounted for in microsimulation modeling.

Newhouse, et al., presented their finding on the effect of a plan's cost-sharing on prescription drugs in this way: “[O]ther than through its effect on [physician] visits, plan did little to alter drug use; that is, plan did not much affect either the physician's tendency to prescribe for a patient in the office or the patient's tendency to fill the prescription. ... [A]lthough we saw evidence of medically inappropriate overprescribing, the proportion of inappropriate prescribing did not vary much by plan design. ... [C]ost-sharing reduced the use of both prescription and

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<sup>38</sup> **Figure 5** of CRS Report RL31374, *Health Expenditures in 2003*, by Paulette C. Morgan [<http://www.congress.gov/erp/rl/pdf/RL31374.pdf>]. The HIE plans covered prescription drugs which at the time had “traditionally been poorly covered by health insurance plans. ... (A)bout 8 percent of total spending [in the HIE] was for drugs” (from Newhouse, et al., p. 365). This may have been higher than the average for that time because of the HIE coverage.

nonprescription drugs; there was no evidence of substitution of over-the-counter drugs for prescription drugs as cost-sharing increased” (p. 365).

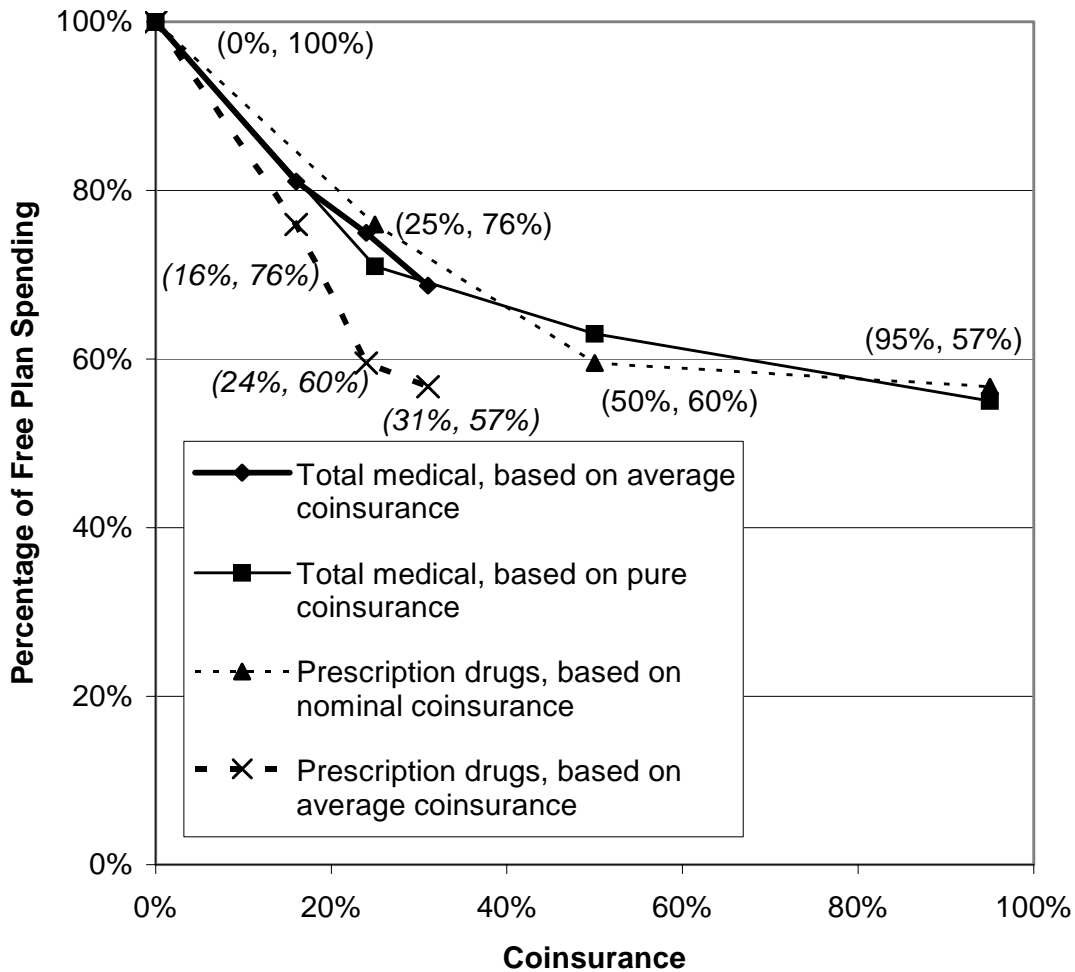
These statements would suggest that the effect of cost-sharing on prescription drug spending would be similar to that of total medical care, or outpatient care more specifically. Other HIE results indicate that prescription drugs are quite different, depending on one’s interpretation. To understand this, it is helpful to recall the discussion of the effect of cost-sharing on *total* medical care in the section presenting selected HIE results. **Figure 4** showed the association between cost-sharing and spending in the original HIE plans, which had out-of-pocket maximums. However, because of the out-of-pocket maximums, the nominal coinsurance failed to capture all of cost-sharing in the plan. A separate estimate was derived by the HIE authors to determine the “pure price effects” associated with the HIE coinsurance levels, shown as “Without out-of-pocket maximum” in **Figure 4**. The adequacy of these numbers was affirmed by how they lined up with the average-coinsurance results, shown in **Figure 5**, although the analysis was limited in that the average coinsurance levels did not exceed 31%.

All three sets of estimates — based on nominal coinsurance, average coinsurance, and pure coinsurance (or pure price effects) — are not available for prescription drugs. For purposes of this report, the last would seem most important, which is the piece not contained in the HIE results. The other two sets of estimates for prescription drugs are shown in dashed lines in **Figure 13** along with the original total-medical lines from **Figure 5**. The lighter dashed line in shows the relation between *nominal* plan coinsurance and prescription-drug spending. The darker dashed line uses the same prescription-drug spending levels but is based on the *average* plan coinsurance. The points labeled in the figure are only for the prescription-drug lines. No amounts were given for pure coinsurance, or pure price effects, for prescription drugs. Lacking this, the other two sets of estimates must be used to judge whether the total-medical values are adequate estimators for prescription drugs.

As shown in **Figure 13**, the nominal coinsurance for prescription drugs corresponds with the average- and pure-coinsurance levels for total medical spending. Prescription-drug spending based on the average coinsurance appears much different than for total medical spending. This would seem to lead one to a different conclusion than that of the HIE authors. The comparisons in the figure may be suspect, however. For example, the average coinsurance for the dark, dashed line in the figure is for *all* medical spending, not specifically for prescription drugs. This is problematic because the average coinsurance specifically for prescription drugs may be different, particularly if a disproportionate share of prescription-drug spending took place below the out-of-pocket maximum, which is believable. If most prescription drug spending took place below the out-of-pocket maximum, then the nominal coinsurance would be closer to the actual average cost-sharing for prescription drugs than would the plan’s total average coinsurance. In that case, the *lighter* dashed line may be preferred. This would be consistent with the HIE authors’ conclusions. It would also make calculating the effects of cost-sharing simpler, since the total-medical values could be used for all types of care, including prescription drugs.

It is difficult to determine from the HIE what the pure price effects are on prescription drug spending. Even if it were possible to determine, it would be questionable as to its applicability today. In lieu of any more recent experimental information, it is arguable that using total medical factors is no worse than any of the other options, especially considering the potential challenges of appropriately applying additional factors in microsimulation modeling.

**Figure 13. Effect of Coinsurance on Annual Per-Person Total Medical and Prescription Drug Expenses, as a Percentage of Free Plan Expenses**



**Source:** Figure 5 and Congressional Research Service (CRS) calculations from Newhouse et al., *Free for All? Lessons from the RAND Health Insurance Experiment* (Cambridge, Massachusetts: Harvard University Press, 1993), particularly Table 5.13.

## Conclusion

Arc elasticities and induction factors are used in health policy circles to replicate results from the RAND Health Insurance Experiment (HIE). This report showed how both methods have serious limitations, particularly for their practical applications in microsimulation modeling.

Results based on arc elasticities are problematic when dealing with a plan, or even a record in a dataset, in which there is no cost-sharing. (Results from point elasticities are not even calculable from a plan with no cost-sharing, which is one reason why point elasticities were quickly dispensed with in this report.) If such a free plan is used in applying a particular arc elasticity, total spending will be adjusted by a constant percentage, regardless of the cost-sharing in the non-free plan. A workaround was presented, adding another level of complexity to the application of arc elasticities, but its appropriateness is questionable.

Induction factors can handle such free-plan information. Unfortunately, their values are not reversible. Between two price-quantity points, *two* induction factors emerge rather than one. This complicates the appropriate application of induction factors.

One purported advantage of induction factors is that they can better handle complicated plan structures. This is because they are calculated and applied based on the *dollar* amounts of cost-sharing that individuals face in a plan. In addition, induction factors predict spending by applying the new cost-sharing structure to the *old* total spending, which also makes its application easier. The analysis in this report showed, however, that the induction factors essentially rely on the average coinsurance calculated from applying the original total spending to the new cost-sharing structure. Arc elasticities do so as well with concomitant limitations acknowledged. That induction factors effectively do the same thing, with the same concomitant limitations, is typically obscured because the induction factors rely on the nominal dollar amounts. Thus, in actuality, induction factors have no inherent, substantive advantage for handling complicated plan structures. Indeed, because of their use of dollar cost-sharing based on the original total spending, the induction factor is arguably inferior when dealing with pure-coinsurance plans, upon which the HIE results in this report were based. This removes the primary rationale for tolerating the induction factors' lack of reversibility.

The CRS/Hay models create and use a baseline of free-plan values for thousands of records/individuals. Although arc elasticities and induction factors can be used for this purpose, their sensitivity to the specific factors' values in such circumstances is additional cause for concern. Special care must be taken to use the appropriate values. Because the CRS/Hay models currently use induction factors, which are not reversible, using the appropriate values is even more important and involved. Presently, however, the models use constant values for the induction factors regardless of coinsurance levels.<sup>39</sup> Either new factors should be used that vary by

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<sup>39</sup> An adjustment has been built into the models based on the dollar amounts of cost-sharing, (continued...)

coinsurance or a new method should be applied. Arc elasticities are not superior for this purpose, given the method's limitations and the models' use of free-plan values.

In an effort to apply some method that would be particularly useful for microsimulation modeling, the cubic formula was derived. Its legitimacy is based on the notion that a person's experience in a plan as captured by their average coinsurance is appropriate for replicating HIE results. The cubic formula has many of the desirable qualities that arc elasticities and induction factors sometimes lack. The cubic formula is path neutral. Because it does not have separate factors that must be calculated, the cubic formula has no issues regarding reversibility. The cubic formula faces no diminution of predictive power when dealing with free-plan information. In addition, from a practical standpoint, it is much simpler to appropriately implement in microsimulation modeling.

The key flaw of the cubic formula is that if one wants to separately model the impact of cost-sharing changes by type of service (for example, inpatient versus outpatient), new cubic formulas must be derived, as was done in this report. At least one of these cubic formulas produced quite undesirable results. The cubic formula for inpatient care estimated that as coinsurance rises between 41.4% and 69.6%, there would be *higher* inpatient spending. While there are no HIE results between its four original data points, this result is counterintuitive.

The HIE results also showed that, for most cost-sharing levels, there is little or no difference in total spending resulting from separate application of cost-sharing factors for certain types of medical care. Even for prescription drugs, the type of health care popularly believed to be most affected by cost-sharing changes, the HIE does not provide evidence that people respond dramatically different to changes in cost-sharing compared to other types of care. This being the case, it is arguable that the cubic formula for total medical is adequate for predicting all kinds of cost-sharing changes. Moreover, because predicted values can vary more from the cost-sharing method used rather than the type-of-service variation, the choice of cost-sharing method is arguably more important than dealing with type-of-service variations.

None of these methods — arc elasticities, induction factors, the cubic formula — is perfect. Each has its advantages. Each has its flaws. Analysts face the decision, given the advantages and flaws of each, of which is best for their purposes. For the CRS/Hay models, which are presently built on a baseline of free-plan values and use constant induction factors regardless of cost-sharing, the cubic formula appears better able to replicate HIE results than the current approach.

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<sup>39</sup> (...continued)

but this should have little or no impact on replicating the HIE results (or if there were an impact, it would not be for this purpose), which vary by coinsurance regardless of the nominal dollar amounts of cost-sharing.