State of Arkansas
Arkansas Insurance Department

Arkansas Marketplace Report

Version 2.0
August 31, 2011

First Data
b›yond the transaction

Membership and cost projections are necessarily forward-looking. While the values and assumptions within these models are based on our best available information, techniques, and applicable experience, we cannot warrant their accuracy as events unfold.

Table of Contents

1.0 Introduction

This report describes the implementation and results of statistical models used to estimate participation and other variables in the Arkansas Health Benefits Exchange (HBE). The models are developed and estimated by Mark Howland, Tom Messer, and Lawrence Powell, under the leadership of David Sodergren and Jim Glick of First Data.[1]

In addition to accepted actuarial and econometric techniques, the modeling process included interaction with the Steering Group and feedback from several Working Groups involved in the planning process. We made every effort address concerns and suggestions from each group. A list of frequently asked questions and answers about the models and modeling process is available. We hope this interaction serves to bridge the gap of understanding between our rather technical models and the concerns of stakeholders without actuarial or econometric expertise.

The final projections are generated by the combination of a micro simulation model and an actuarial model. The simulation predicts patterns of behavior as a result of changes in public policy from 2013 to 2014. The actuarial model uses state and national estimates from various sources to predict consumption of medical care and changes in annual program participation from 2014 to 2019.

Statistical models are necessarily complex. We intend for this report to be sufficiently detailed that the reader may understand results of the models, but it is not meant to be an academic treatise on the topic of simulation models or actuarial estimates. Readers may review extant literature for enrichment materials on the specifics of such models.

Results from the models indicate approximately 211,000 Arkansans will enroll in the non-Medicaid HBE programs in 2014. From 2014 to 2019, enrollment in the exchanges is expected to increase to approximately 292,000. In addition, Medicaid enrollment is expected to climb from 682,000 in 2013 to 857,000 in 2014.

1 The authors also thank Cal Kellogg, Sam Partin, and the actuarial staff of Arkansas Blue Cross Blue Shield for their helpful input.

Then, from 2014 to 2019, 42,000 additional Medicaid recipients will be added for a total of 899,000. Table 1 describes participants in Arkansas' health benefits exchange in more detail.

Table 1: Arkansas Health Benefits Exchange Participants: 2014

Individual & SHOP Exchanges (total)		210,755
Insured status:	Previously uninsured	120,290
Gender:	Male	106,346
	Female	104,409
Age:	0-4	19,113
	5-18	56,821
	19-25	17,175
	26-35	32,349
	36-45	42,164
	46-55	25,376
	56-64	15,884
Family Income as % of Poverty:	139-150%	18,402
	151-200%	23,051
	201-250%	58,113
	251-300%	34,351
	301-400%	58,823
	>400%	18,015

We organize the remainder of this report as follows. In Section 2 and Section 3, we describe the simulation and actuarial models, including data sources, assumptions, and basic steps. In Section 4, we present and discuss results of the models.

2.0 The Health Benefits Exchange Micro Simulation Model

The concept of a health insurance reform micro simulation model originated in the late 1980's with the advent of computers and statistical techniques capable of efficiently estimating the required steps. Since then, several proprietary models have emerged from various think tanks, consulting firms, government agencies, and academics. Among the more notable authors are the Urban Institute, the Lewin Group, Rand, and the Congressional Budget Office (CBO). This model draws from sections of existing models, but it also includes unique aspects allowing us to apply it to the demographics of Arkansas.

Our micro simulation model simulates behavior of a population in response to changes in health insurance markets. It uses a series of equations, randomized simulations, and rule applications to glean unbiased results from available data. In this instance, we are concerned with purchasing behavior in the Arkansas. The basic steps involved in model estimation appear in Table 2.

Table 2: Basic Steps in Micro Simulation Model Estimation

1) Assemble the appropriate data
2) Estimate healthcare expenditures for each family and individual
3) Estimate health insurance premiums for each family and individual
4) Estimate elasticity of demand for HBE coverage
5) Estimate cost differentials from subsidies and selection
6) Use the elasticity estimate and cost differentials to predict probability of purchasing coverage if eligible
7) Apply eligibility rules to individuals expected to purchase coverage
8) Simulate Arkansas's employment market, workers, spouses, and dependents
9) Use employer cost differentials and penalties to predict group participation in the HBE
10) Apply eligibility rules for groups in the HBE
11) Calculate point estimates

The first step is to assemble appropriate data to use in steps two through eleven. We collect data on health insurance coverage status and several demographic variables from the February and March supplement files of the Current Population Survey[2] (CPS)[3]. We merge the two files via the process described by Blumberg, *et al.* (2003). We collect data on health expenditures from the Agency for Healthcare Research and Quality's Medical Expenditure Panel Survey

[2] The Current Population Survey (CPS) is a monthly survey of about 50,000 households conducted by the Bureau of the Census for the Bureau of Labor Statistics. The survey collects core data elements each month and certain other sets of variables at other intervals. In this model, we use the February and March surveys from 2001 and 2005 because they are the most recent surveys including the necessary data.

The CPS is the primary source of information on the labor force characteristics of the U.S. population. CPS data are used by government policymakers and legislators as important indicators of our nations's economic situation and for planning and evaluating many government programs. They are also used by the press, students, academics, and the general public. For more information, see http://www.census.gov/cps/.

[3] We pool CPS data from survey years 2001 and 2005. These are the most recent data including all necessary information.

– Household Component[4] (MEPS-HC)[5]. Then we statistically match these data to the CPS observations using the method described by Blumberg *et al.* (2003). After matching the MEPS-HC expenditures to the CPS file, we delete all observations in states with demographic characteristics substantially different from Arkansas.[6]

Following CBO (2007), we collect data on health insurance premiums from the U.S. Census Bureau's Survey of Income and Program Participation (SIPP). We collect data describing Arkansas's employment structure from the U.S. Census Bureau's Statistics of U.S. Business (SUSB) and from the 2010 Medical Expenditure Panel Survey-Insurance Component (MEPS-IC).

These data represent observations from years 2005-2010. For consistency, we inflate cost measures to real 2013 levels using medical inflation estimates from the published scientific literature. For the years without observed inflation estimates (2011-2013) we also adjust medical costs relative to income with a trending factor of two percent.[7]

We use a system of structural equations to estimate individuals' probability of purchasing insurance from the HBE, if they are eligible. The first equation (Equation 1) is used to match individuals observed in the CPS survey to health expenditure observed in the MEPS-HC survey.

$$\log(HE) = \alpha + \beta`X + \varepsilon \quad \text{(Eq. 1)}$$

The dependent variable, log(*HE*), equals the natural logarithm of health expenditure, alpha is an intercept coefficient, ***X*** is a vector of (many) independent variables, and epsilon is a random error term. We initially fit Equation 1 to MEPS-

[4] The Medical Expenditure Panel Survey (MEPS) is a set of large-scale surveys of families and individuals, their medical providers, and employers across the United States. MEPS is the most complete source of data on the cost and use of health care and health insurance coverage. For more information about MEPS data, see http://www.meps.ahrq.gov/mepsweb/about_meps/survey_back.jsp.
[5] We pool MEPS-HC data from years 2004-2008. Again, these are the most recent complete data available.
[6] This step accounts for observed differences in purchasing behavior across Census regions. The states appearing in our sample are: Alabama, Arkansas, Florida, Georgia, Kansas, Kentucky, Louisiana, Mississippi, Missouri, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia
[7] Two percent is the average difference between medical cost inflation and wage inflation in the most recent five years. This adjustment ensures that medical costs are consistent with real buying power of wages.

HC data using ordinary least squares regression. Next, we apply the coefficient estimates from the model to the CPS observations, yielding estimates of healthcare spending for the CPS population. Then we match the CPS estimate to the nearest MEPS-HC estimate and assign the actual expenditure from that MEPS-HC observation to the CPS observation. Following extant literature, we inflate claims paid by private insurance and Medicaid by 25% to correct for underreporting in the MEPS-HC database.

We also adjust expected health spending of uninsured individuals to match that of similar insured individuals. We do this by repeating the matching process between MEPS and CPS described above with one important change. Uninsured individuals are matched with the most similar insured individual. This step specifically considers the difference in healthcare consumption between insured and uninsured individuals modeled by Pauly (1968).

We use Equation 2 to estimate expected health insurance premiums for insured individuals in the SIPP dataset. First, we delete all observations that do not report spending money on health insurance. Then we fit Equation 2 to the remaining SIPP observations.

$$\log(HI) = \alpha + \delta` X + \varepsilon \quad \text{(Eq. 2)}$$

The dependent variable, log(*HI*), is the natural logarithm of observed health insurance expenditure, and ***X*** is a vector of independent variables expected to explain health insurance cost.[8] We use the coefficient estimates, α and δ, from fitting Equation 2 to estimate expected health insurance premium for each of the observations in the CPS file. For individuals who report health insurance with zero premium (public programs or 100% employer funded) or those who are eligible for, but not enrolled in, insurance with zero premium, premium is set to zero in subsequent calculations.

The next step is to estimate the elasticity of demand for health insurance. In this case, we define elasticity as the expected change in probability of purchasing

[8] Note that the vector, ***X***, in Equation 2 is not the same as ***X*** in Equation 1. Many independent variables appear in the model to improve accuracy of premiums.

health insurance for a one-percent change in the price or cost of health insurance. Because the observed decision to purchase, or not purchase health insurance is a discrete variable, we use a probit model in the form of Equation 3 to estimate the elasticity.

$$P(Y = 1 | X) \text{ (Eq. 3)}$$

or, equivalently

$$y^* = \alpha + \beta`X + \varepsilon, y = 1[y^* > 0] \text{ (Eq. 3.1)}$$

Equation 3 is a conceptual representation of our probit model. It shows that the estimate produced by the model is the probability that Y=1, given observed values of $\boldsymbol{X}$, a vector of explanatory variables. For consistency with Equations 1 and 2, Equation 3.1 presents the probit model as a regression equation. In Equation 3.1, y* is a latent variable with an indicator function of y=1[y*>0]. In other words the discrete dependent variable, Y, is equal to one if an individual purchases health insurance and equal to zero otherwise. The independent variables include the estimates of log(HI) predicted by Equation 1 and a measure of health insurance price.

The health insurance price measure is calculated assuming a "Silver" benefits package with actuarial value equal to approximately 70%. In our data, the parameters of this policy are simply a $1,000 deductible followed by 75%/25% coinsurance until the insured reaches a coinsurance maximum of $3,500 (or out-of-pocket maximum of $4,000). The average actuarial value for our sample is 71%.

The actuarial value calculation requires an estimate of expected healthcare spending. We calculate expected spending similar to the method in Rand (2010). Each individual in the sample is assigned to one of twenty-eight pools. Pools are assigned based on two gender categories, six age brackets, and two health categories. The resulting average expenditure for each pool is assigned to its members as their expected healthcare spending.[9]

[9] Importantly, the expected spending amounts follow intuitive patterns. For example, sick people have higher costs than healthy people, and, with the exceptions of newborns and females in maternity years, medical cost increases monotonically with age.

The price of health insurance (depicted in Equation 4, below) is the sum of expected cost sharing and premiums paid by the insured, divided by benefits paid from the insurance policy.

(Eq. 4)

The probit model is a generalized linear model designed to predict the probability of a bivariate discrete dependent variable given observations of the independent variables. We fit the model to our data using the maximum likelihood estimation technique. We interpret the sum of the coefficient estimates for log(*HI*), and log(*price*) as the elasticity of demand for health insurance. Thus, for a 1% decrease in the cost of health insurance, the model predicts a 0.4% increase in the probability that a person will purchase health insurance. After calibrating the model to best reflect baseline behavior, baseline accuracy is approximately 82% with similar occurrence rates of false positive and false negative.[10]

Next, we apply the elasticity estimates to the change in cost of health insurance if purchased from the HBE. Given the current market regulations in the exchange, there is likely to be substantial cost segmentation. In the absence of a "one price" rule, as insurers enter the exchange, they will differentiate prices from their competitors to increase market share. As a result, HBE consumers will likely be able to find premiums very similar to what they currently pay.

When subsidies are available, the cost of HBE coverage will be lower than that of most alternatives. However, we do not necessarily observe the full cost of health insurance in the SIPP data. We only observe the portion contributed by the employee. While neoclassical economic theory suggests employees *should* consider the entire cost of health insurance; it is clear from the universe of extant empirical literature that employees consider only the portion they must pay in the decision to purchase health insurance.

We estimate new purchase decisions for employees by adding the predicted probability of purchasing health insurance to the products of the estimated

[10] This degree of accuracy is consistent with, or slightly better than existing commercial and academic models.

elasticities and the percent changes in cost and price of health insurance. If this sum is greater than zero, the individual[11] indicates desire to purchase coverage at the HBE price and cost. Otherwise, the employee decides not to purchase insurance. We assume that insured individuals will not voluntarily switch to the exchange unless it offers a premium or price sufficiently lower than what they currently pay. We call the resulting dataset of approximately 41,500 individuals and their insurance purchasing preferences the "donor file."

The next step in the model is to simulate Arkansas's employment market, employees, and their dependents. First, following the Arkansas data reported in SUSB, we create 66,668 employer establishments with 1,020,879 empty employee slots. Next, we populate the worker slots by random sampling (with replacement) from the donor file. We stratify the sampling process by industry, firm size, and whether or not the employer offers health insurance to its employees. Finally, we merge individuals into their families, creating a synthetic family for each working adult. Working spouses are already in the dataset; however, they can be treated as a dependent spouse in one synthetic observation and as a worker with a dependent spouse in another synthetic observation.

Within each employer establishment, employees express their desire for coverage in the exchange versus current coverage (or lack thereof) in what we call a voting mechanism. The probability that an employee will wish to buy coverage in the exchange is averaged across all employees in an establishment. If this number is positive, the employer will choose from available options. For example, if the group exchange is less expensive than the current employees' coverage, employers will choose the group exchange. If it is less expensive for employers to drop coverage, pay any required fine, and have employees purchase coverage in the individual exchange, they will choose this option.

[11] It is important to note that, while children are "behaving" in the model, the factors relevant to the decision (and thus the decision itself) are drawn from the children's parents (e.g. income, occupation, etc.).

3.0 Membership Movement and Cost Model

The micro simulation model described above is well-suited to predict a point estimate of participation, but less so for smaller changes in participation and usage. Therefore, we employ a separate model to estimate membership movement and cost.

The beginning (2013) inputs of the model are taken from several sources of data including National Health Expenditures (NHE), Medical Expenditure Panel Survey (MEPS), Arkansas Medicaid Program Overview for state fiscal year 2010, proprietary SCIOinspire (formerly known as Solucia) studies, and actuarial estimates. Importantly, these beginning estimates are the same as those used in the micro simulation model. The estimates for 2014 are a combination of results from the behavioral model and weighted assumptions from other national studies imposed on Arkansas data. In each instance where non-Arkansas data are used, the weighting of Arkansas data represents more than half of the final outcome.

We estimate changes in participation levels of each group using a combination of expected changes in population demographics, the cost of healthcare, behavior from other published studies, and analysis of proprietary data.

The document that accompanies the empirical migration and cost model explains some of the assumptions and calculations in more detail.

4.0 Discussion of Results

Our combination of two models estimates the expected participation in each type of insurance available after provisions of PPACA take effect in 2014 and changes in these groups from 2014 through 2019. Table 3 summarizes the first year outcomes from implementing the exchanges and expanding Medicaid.

Expanding Medicaid eligibility to Arkansans with income below 139% of the federal poverty level is expected to make this coverage available to 925,000 people in 2014. Existing studies find that not all eligible Medicaid beneficiaries enroll in Medicaid coverage. Our estimate is that there will be 234,000 individuals who were uninsured in 2013, but who would be eligible for Medicaid under 2014 rules. We apply the factor estimated by the Lewin Group (2011) of 71% given the careful treatment of Medicaid take-up in their model. This yields approximately 166,000 additional Medicaid participants plus the 682,000 actually enrolled in 2013. In addition there will be 1% growth in total eligibles which results in 857,000 members with average per member per month (PMPM) medical costs of$557.08.

Results of our models indicate nearly 211,000 people will participate in the two health insurance exchanges in 2014. Approximately 116,000 will be in the individual exchange and 95,000 will be in the group exchange. This includes 120,209 individuals who were previously uninsured. The PMPM cost in the individual exchange is expected to be $399.59, while that of the group exchange is expected to be $394.13.

One result of implementing these programs will be to reduce the expected uninsured population of 20% in 2013 to just more than 10% in 2014. In the projected years that follow, as more people become familiar with these programs, we expect the uninsured population to drop as low as 9% of the population in 2019. Table 4 displays the expected changes in participation and cost for each section of the insurance market from 2014 through 2019.

Table 3: First Year Effects of Exchange

	2013		2014	
2014 outcomes	Membership	Cost PMPM	Membership	Cost PMPM
Medicaid/Arkids Total	682,000	$522.07	857,000	$557.08
Total Exchange Population	N/A	N/A	210,755	397.09
Individual Exchange Total	N/A	N/A	115,925	399.59
From Groups <51			3,767	
From Nongroup Insured			22,047	
From Uninsured Individuals			86,811	
From CHIP/PCIP			3,300	
Groups Exchange Total	N/A	N/A	94,830	394.13
From Insured Groups<51			48,710	
From Insured Groups 51-100			12,641	
From Uninsured Groups			33,479	
Uninsured Total	587,000	433.70	303,177	511.44
Uninsured Group Eligible	80,000	405.00	46,521	
Uninsured Medicaid Eligible	234,000	540.00	70,470	
Uninsured Individuals	273,000	351.00	186,186	
INSURED INDIVIDUALS	136,000	391.50	113,953	410.51
INSURED IN GROUPS <51	289,000	333.00	236,523	346.45
INSURED IN GROUPS 51-100	75,000	351.00	62,359	365.80

Source: Authors' calculations from models described above

Table 4: Changes in Membership & Cost 2014 – 2019

	2014		2015		2016		2017		2018		2019	
	Membership	PMPM	Membership	PMPM	Membership	PMPM	Membership	PMPM	Membership	PMPM	Membership	PMPM
MEDICAID/ARKIDS	857,000	$ 557.08	869,000	$ 590.77	913,000	$ 607.61	892,000	$ 657.61	895,000	$ 699.48	899,000	$ 746.36
INDIVIDUALS EXCHANGE	115,925	399.59	132,605	421.60	156,791	447.37	190,150	462.88	203,494	481.00	205,162	506.36
GROUPS EXCHANGE	94,830	394.13	95,387	415.84	94,050	441.26	93,048	456.56	92,491	474.43	92,992	499.45
UNINSURED	303,177	511.44	285,029	539.62	275,421	572.60	283,962	592.45	286,097	615.64	281,827	648.11
INSURED INDIVIDUALS	113,953	410.51	103,786	433.12	93,427	459.60	82,875	475.53	72,130	494.15	61,193	520.20
INSURED IN GROUPS <51	236,523	346.45	267,912	365.53	234,579	387.88	232,079	401.33	230,690	417.04	231,940	439.03
INSURED IN GROUPS 51-100	62,359	365.80	62,725	385.95	61,846	409.54	61,187	423.74	60,821	440.33	61,151	463.54

Source: Authors' calculations from models described above

5.0 Interactive Model

An interactive model that closely approximates the above results and instructions on its use are attached. This model allows the user to alter various input parameters and assumptions to measure their effect and to create scenarios.

Arkansas Model
v20110830 embedde

Arkansas Exchange
Migration Model.docx

6.0 References

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