PIERCE ATWOOD LLP
ATTORNEYS AT LAW

Christopher T. Roach

One Monument Square
Portland, ME 04101

207-791-1373 voice
207-791-1350 fax
croach@pierceatwood.com

pierceatwood.com

July 9, 2008

Dirigo Health Agency
Attn: Ruth.A.Burke@maine.gov
Dirigo Health Agency
53 State House Station
Augusta, Maine 04333-0053

In Re: Determination of Aggregate Measurable Cost Savings
For The Fourth Assessment Year (2009)

FILING COVERSHEET

Dear Ms. Theberge:

Enclosed for filing please find the following:

SUBMITTED BY:	Christopher T. Roach
DATE:	July 9, 2008
DOCUMENT TITLE:	Non-Confidential Version of Prefiled Testimony of Vincent Maffei
DOCUMENT TYPE:	Prefiled Testimony
CONFIDENTIAL:	**NO**

Thank you for your assistance in this matter.

Very truly yours,

Christopher T. Roach

NON-CONFIDENTIAL

STATE OF MAINE
DIRIGO HEALTH AGENCY

IN RE:	)	EXHIBIT 3
	)	
DETERMINATION OF AGGREGATE	)	
MEASURABLE COST SAVINGS FOR	)	PREFILED TESTIMONY OF
THE FOURTH ASSESSMENT YEAR	)	VINCENT MAFFEI
(2009)	)	
	)	
Docket No.	)	
	)	July 9, 2008
	)	

NON-CONFIDENTIAL

Q. Please state your name and your position with WellPoint, Inc.

A. My name is Vincent Maffei and I am a Senior Biostatician and Health Economist in the Advanced Analytics and Innovation Department in WellPoint's Connecticut office.

Q. Please describe any relevant experience that qualifies you as a witness in this proceeding.

A. As reflected in my curriculum vitae, attached to this testimony as Maffei Exhibit A, I received my Bachelor of Arts degree in economics from Rutgers University in 1973, and my Masters degree in economics from Rutgers in 1980. I also completed all graduate courses and PhD qualifying exams in the PhD program of the Department of Economics at New York University. Before joining WellPoint in 1987, I was an Assistant Professor at William Paterson University and taught courses in finance, econometrics, statistics and economics. In my position at WellPoint, I am responsible for predictive modeling, econometric forecasting of health care costs and membership, economic forecasting, testing, hypotheses on health care/cost interventions, provider evaluation and outcome analysis.

Q. Please summarize your background and experience that qualifies you to provide this testimony.

A. My background in both econometric forecasting and health economics uniquely qualify me to opine on whether the regression methodologies proposed by the Dirigo Health Agency ("DHA") satisfy the scientific standards applicable to regression analyses and in the first instance are appropriate to determine the aggregate measurable cost savings that are within the Dirigo Health Reform Act ("AMCS").

For the first 14 year of my working career I taught statistics and econometrics at William Paterson, Rutgers, and other Universities. At WellPoint, I have spent the last 20 years testing hypotheses about health care interventions, as well as modeling and forecasting health care costs. I have also had the opportunity to expand my learning at professional conferences. Additionally, I have also been a presenter at some of those conferences. My presentations to Actuaries have included how to properly run regressions and do tests of hypotheses, and also how to avoid the common mistakes and pitfalls in both. In practice I have been instrumental in developing econometric models that forecast health care costs and membership for WellPoint states. These models have been tested for accuracy and found reliable. They are now routinely run every month in every WellPoint state for every large block of business. My tests of hypotheses and estimates of savings on internal and external cost of care interventions have been relied upon by WellPoint's management to decide whether or not to continue funding programs and set rate reductions in anticipation of savings.

Q. What is the purpose of your testimony?

A. The purpose of my testimony is to (1) provide background on the elements in and purpose of a statistical regression; (2) explain the concept of statistical significance and the test of hypotheses that determine if the estimated coefficients are reliable; (3) evaluate the regression equations advanced by DHA's consultant schramm raleigh Health Strategy ("srHS") and explain (a) how model mis-specification and violations of regression requirements render as invalid the srHS model, the statistical results and the conclusions drawn from those results, and (b) where the critical Maine Dirigo variables used in the regression fail the most basic statistical test of significance; and (4) evaluate the appropriateness of the sample/cluster utilized by srHS to estimate the coefficients that are used to calculate Dirigo "savings."

Q. Have you reviewed srHS proposed regression analysis?

A. Yes.

Q. Please summarize your opinions of that analysis.

A. 1) srHS uses an approach that has been used previously to analyze individual hospital costs. This approach, however, is inappropriate to model an entire health care system and leads to invalid results. Moreover, the srHS regression analysis is fatally flawed and cannot be considered as a valid measure of cost savings that result from Dirigo. The variable "Dirigo" is in fact neither the "Dirigo Health Reform Act" or the "Dirigo Health Agency." It is, instead, simply a variable that separates the data into two time periods: the period up to and including state fiscal year 2003 and the period after state fiscal year 2003. In addition, the equations include variables which are not statistically significant and should have been removed from the final model. Instead, those statistically insignificant variables (MĐD and MĐYĐD) which were critical for Dirigo savings were retained and used in the calculation of "Dirigo" savings. The srHS approach, accordingly, is not valid.

2) In addition to including variables that should have been removed using proper statistical techniques, both the U.S. and the Cluster 1 models fail to include economic and financial variables that are important drivers of costs in a healthcare system--variables such as employment growth and hospital operating margin. The omission of important explanatory factors can very well lead to biased estimates for the coefficients of the included variables (*i.e.*, the impact of the omitted variables can be falsely correlated to the variables that were included).

3) For a regression to be appropriate for an analysis, the random component (*i.e.*, the error terms) must be "independently and identically distributed," referred to herein as "iid." The srHS regression used pooled time series and cross-sectional data. Since autocorrelation (where the error term in one time period influences the error term in the ensuing period) is a common problem in time series data, researchers using time series data should always test for and correct for autocorrelation. To my knowledge srHS did not test for autocorrelation. Heteroskedasticity (where the variance of the error term is typically proportional to the value of the dependant or some explanatory variable) is a common problem in cross-sectional data. Researchers using cross-sectional data should always test for and correct for heteroskedasticity. To my knowledge srHS did not. Additionally, the error terms for all hospitals in each state are correlated since hospitals within a state react to changing state economic and regulatory conditions in a similar manner. The violation of the iid assumption renders the t statistics from the regressions invalid.

4) Additionally, the Cluster 1 "sample" that was selected has undesirable and unusual characteristics that make it a poor choice as a sample or benchmark. Worse yet is the manner in

which Cluster 1 was selected. srHS selected states where (we are told) the coefficients of some of the dependent variables are similar to those for Maine. Because srHS selected observations that are similar the resulting error terms (actual value minus predicted) are not independent. These error terms are used to calculate the standard errors in the regression output. The standard errors are used to calculate the t statistics. The t statistics are used to determine statistical significance. If the error terms are correlated then the standard errors will be biased estimates (biased downwards) of the true variance. The t statistics (that standard statistical software automatically generate) will be overstated and, accordingly, those statistics are invalid to determine the statistical significance of the regression results. Any conclusions about Maine drawn from the Cluster 1 sample are simply invalid.

Below I will describe these flaws, each of which independently would render the srHS model highly suspect, but together demonstrate that the model put forward by DHA is simply not valid.

Q. Before explaining how the critical srHS regression results are statistically insignificant, please explain the purpose of a statistical regression.

A. A statistical regression is commonly used for hypothesis testing, estimation, and forecasting. The advantage of using a properly specified multi-variate approach (***i.e.***, regression) over a univariate approach (such as pre and post comparison of average cost) is that the multi-variate approach provides an opportunity to account for the multitude of other factors that may be correlated with changes in the dependent variable (***e.g.***, average cost). The statistics generated by the regression calculations enable us to apply the basic hypothesis test to every explanatory variable: Does that variable influence the dependent variable or does it have no effect? In the case of the regression analysis proposed by the Dirigo Health Agency through srHS, the question is whether the purported explanatory variable labeled "Dirigo" (in reality a pre/post SFY 2003 variable) and MĐD, and MĐYĐD have any correlation to the dependent variable, CMAD cost. By casting variables as 'explanatory' the developer of the model presumes causality. Unfortunately, the regression analysis merely merely detects correlation between dependant and explanatory variables, it does not prove causality.

Q. What do you mean that the developer of the model presumes causality?

A. It is improper to suggest that regression analysis is capable of determining attribution or causal effect. Instead, we can only say that a regression on a properly specified model that fullfills all the fundamental asumptions underlying the regression methodology can establish a correlation between a target variable (i.e. the 'dependant' variable) and the "explanatory" variables. This may provide support for a hypothesis about causality, but it does not prove it. By placing an important factor on the right hand side of the regression equation and referring to it as an "explanatory" variable most researchers assume that changes in the right hand side variables "cause" changes in the left hand (i.e. dependant) variable. Unfortunately, too many researchers assume that statistical evidence of correlation proves causality. All too often subsequent research has shown that both the dependant and independent variables moved in response to a third unknown or unobserved variable. Many a forecaster has discovered that while the relationship between the unobserved causal variable and the supposed explanatory variable was constant for the estimation period, this relationship diverged in the forecast period. Since the forecaster had unknowingly attributed causality to the wrong variable, his predictions were incorrect.

Q. What do you mean by "properly specified"?

A. "Properly specified" in the context of a regression analysis means that the model must include all factors or events (in their appropriate mathematical form and with the correct lag time for their impact) that could have an impact on the dependant variable (again, in this case, the dependent variable would be the cost per CMAD). Omission of a factor which has an appreciable impact on the dependant variable will not only represent a missed opportunity to more accurately estimate (or forecast), it may well lead to biased estimates of the coefficients of the included explanatory variables. Put differently, if the regression analysis mis-specifies the factors that are necessary to measure the dependent variable, the analysis will be inherently unreliable. Some or all of the impact of the omitted variables can be assigned to the included variables generating biased estimates of the true impact of the included variables.

It is also important that factors or events that have no appreciable impact on the dependent variable be excluded from the final form of the model. Since it is almost impossible to determine in advance which of the many candidates for "explanatory factors" are legitimate, the only way to determine which variables are legitimate is to try all logical candidates in the regression and to evaluate the resulting t statistics.

Q. Before continuing with your testimony, please explain what a "coeffient" and "t statistic" are in the context of a regression analysis.

A. A "coefficient" in a regression analysis is the estimated value which tells us how many units the dependent variable will change (and in the positive or negative direction) in response to a one unit change in the explanatory variable with which the coefficient is associated. A "t statistic" in a regression analysis is used to calculate the statistical significance of the coefficient. It tells us if the coefficient could have been generated by random variation, or if there is little chance that random variation could have generated the value. If the coefficient is large relative to the random variation associated with the explanatory variable (given by the Standard Error in the regression output) then there is little chance that random variation could have generated such a relatively large value, and the absolute value of the t statistic will exceed the critical level associated with statistical significance. For completeness sake the formula for a t statistic is:

$$t = \frac{((Estimated\_Coefficient) - (Hypothesized\_Value))}{StdError}$$

Where the Hypothesized Value = 0 (*i.e.*, there is no relationship between dependent and explanatory variable) is the basic hypothesis that is used to generate the probability (or significance) figures in all standard regression output.

Q. How do you determine which candidates for explanatory factors are legitimate?

A. The inherent randomness in numerical measures assures that there will always be at least some spurious correlation between any two variables. By way of example, the the number of black flies per acre in the northern Maine woods and the daily closing prices of the Dow Jones Industrial Average will often show some correlation notwithstanding that they are entirely unrelated variables. It is common to refer to correlation generated by random variation as spurious correlation. Any spurious correlation between a dependent variable and potential explanatory variable will increase R^2. R^2 is a measure of how much of the variation in the dependent variable is accounted for by changes in the explanatory variables. (R^2 ranges in value from 0 to 100%.) To validate a regression analysis, statisticians need to ensure that the estimated relationship between the dependent and explanatory variable (*i.e*, the estimated coefficient) is stronger than that which can be generated by spurious correlation. The customary method is to evaluate the t statistic associated with each explanatory variable. This amounts to a test of the hypothesis that the explanatory variable has no more effect on the dependent variable than could be explained by random variation. Keeping with our example, a statistician would analyze whether the t statistic associated with black flies has an effect on the Dow Jones prices greater than that which is generated by random variation. It is customary to reject that hypothesis and keep the explanatory variable in the model only if the absolute value of the t statistic is large enough to indicate that there is less than a 5% chance that the value of the coefficient could have been generated by random variation. If there is at least a 5% chance that the value of the coefficient could have been generated by random variation, that explanatory variable is deemed to be statistically insignificant (*i.e.*, invalid as a factor that may explain change in the dependent variable).

Q. Is the R^2 test alone sufficient to evaluate the validity of a model?

A. No, R^2 alone is not sufficient to evaluate the validity of a regression model. As previously mentioned, R^2 will always increase even if there is only weak, spurious correlation between dependent and additional explanatory variables. Indeed, the concept of adjusted R^2 (sometimes referred to as "R bar squared") was developed to counter the tendency of some researchers to include too many "explanatory" variables in order to increase R^2 and give them reason to claim that the results are better than they truly are. If, in sucessive runs of a regression, adding one additional explanatory variable at a time, R bar squared does not increase, that is an indication that the relation between the dependent and the additional explanatory variable is so weak that it could be generated by spurious correlation or a high degree of multi-collinearity.

A better way to evaluate a model is to use a hold out sample (a.k.a. split sample). The 50 states could have been divided into two <u>randomly</u> selected samples of 35 and 15 (or 30 and 20). The coefficients of the model are then estimated using the larger sample and then applied to the smaller sample. Commonly accepted measures of predictive accuracy (**R**oot **M**ean **S**quare **E**rror favored by econometricians or **M**ean **A**bsolute **P**ercentage **E**rror favored by Actuaries) can be applied that evaluate the prediction error (actual value minus predicted) in the hold out sample. A good model is one that explains well in the sample used to estimate it and predicts well in the hold out sample. A model that explains well in the estimation sample, but does not predict well in the hold out sample is a poor model. Models that do not explain well in the estimation sample, but predict well in the hold out sample do so by fortutious accident. Needless to say, they are not good models.

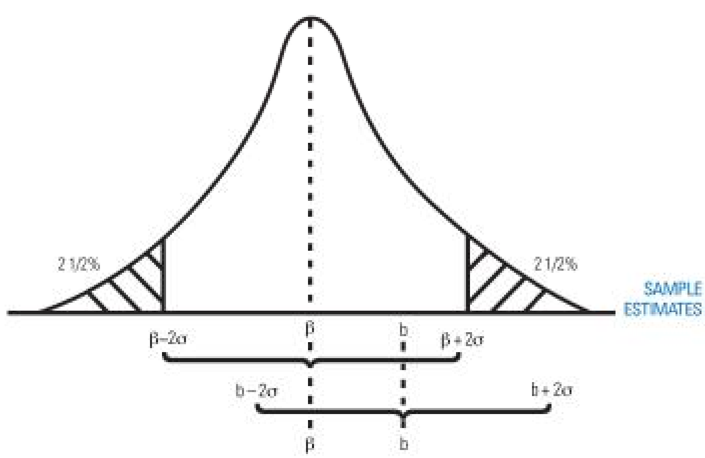
Even if the RMSE or MAPE indicate good model performance, the Dirigo savings still require unbiased estimation and statistical signifance for the M**Đ**D and M**Đ**Y**Đ**D terms. Without unbiased estimation and statistical signficance in those key variables, the model cannot (and does not) produce valid results.

Q. What is multi-collinearity?

A. Multi-collinearity results when two or more explanatory variables move in unison. It is often impossible to separate out the individual impacts. Usually what happens is that the calculations assign one of the co-linear variables the impact of both variables while the coefficient of the other variable appears as statistically insignificant. This means that if there is a high degree of multi-collinearity, the regression analysis may yield biased correlative results to one of the co-linear variables.

Q. Why do statisticians generally agree that there must be less than a 5% chance that the value of the coefficient could have been generated by random variation in order for the explanatory variable to be statistically significant?

A. All the coefficients calculated from sample statistics are only estimates of the true relationship between dependent and explanatory variables. Any sample is but one of many different possible samples that could have been selected. For example, if we randomly take a sample of six of the fifty states, there are millions of different combinations (or samples) that could have been selected. Due to randomness and subtle differences, each sample will generate its own estimate of the true relationship. Even if the true value is zero, those sample estimates will not be zero, they will be distributed around zero (see graph below). Most of the sample statistics will be close to zero but there will also be a number of samples that, because of random quirky combinations, have values notably different from zero.



In the standard 'null' hypothesis $\beta = 0$.

Traditionally we only take one random sample. Unfortunately, we do not know where in the distribution of all possible sample estimates our one sample and its estimated coefficient comes from. However, if the calculated t statistic has an absolute value of approximately 2.0 or greater (1.67 for a one tail test), then we know that there is only a 5% chance or less that we selected one of those quirky samples that lay in the tail of the distribution and has unusually large (or low) sample estimates.

If the t statistic calculated from your randomly selected sample is greater than 2.0, then the traditional conclusion is that, since the probability of getting one of those quirky samples is 5% or less, it is more reasonable to believe that the reason we have a sample estimate of a real (*i.e.*, non zero) association between the dependent and explanatory variable is because the relationship is truly non-zero. If the absolute value of the t statistic is less than 2.0 then the traditional conclusion is that the estimated relation between dependent and explanatory variable is small enough to be explained by random variation. In that event, we have failed to prove that a relationship really exists and the variable should be deleted from the model and other potential explanatory variables investigated.

Q. Will you explain the concepts of the regression equation put forth by srHS and the meaning of the terms used in the equation?

The srHS equation looks at how CMAD average cost changes over time. Time is considered a proxy for explanatory variables that change slowly and consistently over time (*e.g.*, an aging population). The ensuing testimony refers to the following table of statistical output from the srHS regression for all US hospitals for the years 2000 through 2007.

Table 1: Regression Output for Total US Hospital Analysis

	srHS	Dobson | DaVanzo						
		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Intercept)	847.9188	847.9188	105.2954		8.0528	0.0000		
*Maine**	*432.6228*	*432.6228*	*312.0161*	*0.0125*	*1.3865*	*0.1656*	*0.1808*	*5.5313*
Dirigo	285.6101	285.6101	65.0775	0.0624	4.3888	0.0000	0.0722	13.8561
Year	268.5658	268.5658	11.3216	0.2681	23.7216	0.0000	0.1141	8.7630
Total.Beds	0.8724	0.8724	0.0315	0.1186	27.7298	0.0000	0.7975	1.2539
Interns.Beds	4528.4547	4528.4547	50.8485	0.4067	89.0578	0.0000	0.6990	1.4306
Rural.Indicator	-475.1056	-475.1056	25.7348	-0.0778	-18.4616	0.0000	0.8212	1.2177
..Days.Medicare	-1332.4051	-1332.4051	67.5437	-0.0916	-19.7266	0.0000	0.6754	1.4806
..Uninsured	32.4890	32.4890	2.2261	0.0606	14.5943	0.0000	0.8444	1.1842
Wage.Index	4364.3824	4364.3824	88.5942	0.1988	49.2626	0.0000	0.8954	1.1169
*M:D**	*-65.4460*	*-65.4460*	*990.3913*	*-0.0013*	*-0.0661*	*0.9473*	*0.0358*	*27.9588*
*M:Y**	*130.7365*	*130.7365*	*167.0321*	*0.0158*	*0.7827*	*0.4338*	*0.0359*	*27.8371*
Y:D	-61.9550	-61.9550	15.7172	-0.0776	-3.9419	0.0001	0.0376	26.6044
*M:Y:D**	*-32.2186*	*-32.2186*	*236.4283*	*-0.0037*	*-0.1363*	*0.8916*	*0.0199*	*50.2830*

Q. Based on the table above that is reproduced from the srHS model, are any of the explanatory variables statistically significant?

A. Yes. Below I will describe each of the statistically significant variables, what they are intended to determine, their calculated t statistics, and resulting statistical significance. Before doing so, however, I note that none of the variables that are critical to the “cost savings” calculation in the srHS model are statistically significant, which renders the srHS model invalid for that purpose. With that understanding, I will first describe those variables in the srHS model that are statistically significant.

The “Year” variable clicks off the passage of time in annual increments. According to the coefficient estimates in the above table, CMAD rises by an average of $268.57 every year. The t statistic for “Year” (23.72) is so large that there is no question that the correlation between the passage of time and the rise in CMAD is statistically significant. That is, the probability that this coefficient could have been generated by random variation is so small (it does not even register at the 4^{th} decimal in the “Sig” column in Table 1) that it is highly likely that the trend is indeed around $269 per year.

The coefficient for “Total.Beds” indicates that each additional hospital bed adds $ 0.87 to the CMAD average cost. Similar to the “Year” variable, the t statistic for “Total.Beds” (27.73) is so large that there is no question that this coefficient is a good estimate of the real value. Statistically, there is no way the correlation could have been generated by random variation.

The coefficient for “Interns.Beds” (*i.e.*, Interns & Residents per Bed) indicates that each additional Intern or Resident (per bed) adds $ 4528.45 to the CMAD average cost. The t statistic for “Interns.Beds” (89.06) is so large that there is no way that random variation could have generated the result.

The coefficient for “Days.Medicare” (*i.e.*, the ratio of Medicare days to total days) indicates that for every 1% point increase in that ratio lowers the CMAD by $1332.41. The absolute value of the t statistic for “Days.Medicare” (-19.73) is also too large to conclude that random variation generated the result.

The coefficient for “Wage.Index” (*i.e.*, the ratio of the state’s average hourly wage to the national average) indicates that each 1% point increase in that ratio adds $ 4364.38 to the CMAD average cost. The t statistic (49.26) indicates it too is statistically significant.

The coefficient for “Uninsured” (*i.e.*, the ratio of the uninsured population to total population) indicates that every 1% point change in that ratio changes the CMAD cost by $32.49. The t statistic (14.59) indicates it is statistically significant. Since variation in State uninsured rates is very large (ranging from 25% in Texas to 8% in Minnesota) while changes in the uninsured rates over time are very small (typically 1% to 2%), the coefficient of this independent variable reflects how different uninsurance rates explain CMAD costs variation from state to state.

The “Rural.Indicator” is a binary variable. It takes on the value of 1 when the data used are from rural hospitals, and the value zero when the data are from urban hospitals. This binary variable indicates that the trend line for rural hospitals is lower (*i.e.*, there is a vertical downward shift in the trend line for rural hospitals)—but with the same slope (*i.e.*, change over time)—than it is for their urban counterparts. The estimated coefficient indicates that, on average, rural hospitals cost $475 less regardless of year. The absolute value of the t statistic (-18.46) is also too large to conclude that random variation generated the result.

The “Dirigo” variable is another binary variable. This binary takes on the value of 1 when the data used are prior to June 30, 2003 (the end of FY 2003), and the value zero when the data are post June 30, 2003. As with all binary variables, the Dirigo variable generates a one time vertical shift in the trend line. In this case it shifts the trend line for all hospitals <u>in</u> <u>all</u> <u>states</u>. Although labeled "Dirigo", this variable in fact simply divides the data into pre-June 30, 2003 and July 1, 2003 and after. The trend (*i.e.*, the slow and consistent change over time) is unchanged by this binary variable. However, after 2003, there was a one time drop in costs, estimated at $285.61, due to some unique and unspecified event in 2003. (Since the binary has a value of 1 prior to FY 2003 and a value of 0 after, and since the corresponding coefficient is positive, that indicates that the trend line prior to 2003 was $285.61 higher than it was post 2003. However, the slope of both the pre and post 2003 trend lines are unchanged by this binary.) The t statistic (4.39) indicates that the correlation is statistically significant. Because the cost changes are reflected in all states, this srHS equation demonstrates that something nationwide—as opposed to something specific to Maine—has generated a vertical shift in this trend line in 2004.

Q. Before moving on to the remainder of the variables in the table, do any of your calculations of the t statistics or statistical significance involve subjective judgment on your part?

A. No. The interpretation of the t statistics and other standardized output from the regression are not open to subjective judgment. Since the statistical software does not know if the researcher is proposing a one tail or a two tail test, most software outputs probabilities (the "Sig" values in the above table) for a two tail test. A two tail test would be appropriate if the explanatory variable could cause positive or negative changes in the dependent variable. The srHS regression makes the presumption that the Dirigo legislation could only decrease health care costs and could not possibly increase costs. Given that health care related legislation has had a long history of increasing health care costs, I would not make that presumption. That said, presuming, as srHS did, that the Dirigo legislation can only decrease costs, we would need to do a one tailed test. Instead of looking to see if the probability (Sig value) is less than 5%, we need to determine from standard t tables the t value associated with 5% probability in the lower left tail of the t distribution. We would then compare the actual t value to this "critical" t value. If the actual t value is lower than the critical t (larger in absolute value but negative in sign) then we would reject the hypothesis that there is no correlation between the dependent and explanatory variables. That is, the difference between the estimated coefficient and zero are too large to be reasonably explained by random variation.

Q. Having said that, does the table from the srHS regression also contain variables that are statistically insignificant?

A. Yes, there are several and they are critical to the results. Below I will describe each such variable, what it was intended to measure and the results that demonstrate that each is statistically insignificant and therefore should have been excluded from the final srHS model.

The “Maine” variable is a binary variable. This binary takes on the value of 1 when the data used are from Maine, and the value zero when the data are from any other state. This variable represents an attempt to test the hypothesis that CMAD costs are higher in Maine (other factors taken into consideration) than in the rest of the nation (on average). This variable generates a vertical shift in the trend line for Maine hospitals. The trend is unchanged by this binary variable; however, Maine hospital CMAD costs are estimated to be $432.62 higher (on average) than hospitals in any other states in any year. The t statistic (1.39) indicates that this coefficient is not statistically significant. Put differently, this t statistic reflects that there is a greater than 5% chance that the estimated coefficient is generated by random variation. Using standard conventions this variable should have been removed from the final srHS model.

The “M**Đ**D” variable is an interaction term, that is a term used when two or more explanatory variables are multiplied together. In this case the “Maine” binary and the 2003 event binary labeled “Dirigo” are multiplied together. Our use of the earlier Maine binary reflects the assumption that Maine hospital costs are higher than those of other states simply because they are in Maine. This interaction term represents an attempt to test the hypothesis that after FY 2003 there was a one time change in costs (*i.e.*, that did not change the slope of the trend line) that was unique to Maine. The coefficient indicates that the line appears to have shifted by $65.45. However, since the absolute value of the t statistic associated with this coefficient (-0.066) is so small, the result is not statistically significant. This means that the srHS model has not proven that Maine hospital costs experienced a statistically significant one time cost shift after FY 2003. Instead, the estimated coefficient is the result of random variation. This variable should be removed from the final model.

The “MĐY” is another interaction term. In this case, the “Maine” binary and the trend variable “Year” are multiplied together. By introducing an additional trend component (MĐY=Y) for Maine only (for Maine only because M=1 only if the data is from a Maine hospital; M=0 for hospitals from any other state), this interaction term represents an attempt to test the hypothesis that the cost trend (slope of the trend line) has always been steeper in Maine. The estimated coefficient indicates that the slope of the CMAD average cost line is $130.74 (per year) steeper in Maine (2000 to 2007). The t statistic associated with this coefficient is 0.7827, far less than half of what is needed to achieve statistical significance. This means that the srHS model does not reflect that Maine’s costs had been increasing at a rate different from the rest of the nation. The estimated coefficient is the result of random variation. This variable should be removed from the final model.

The “MĐYĐD” is another interaction term. It is generated by multiplying the “Maine” binary (1 for Maine, 0 otherwise) by the “Dirigo” binary (1 for pre June 30, 2003, 0 for post June 30, 2003) by year (the trend variable). By introducing this additional trend component only for Maine and only after FY 2003 (MĐDĐY=Y only for Maine FY 2003 and prior; 0 for any other state and for Maine post FY 2003), this interaction term represents an attempt to test the hypothesis that the cost trend (slope of the trend line) is different after 2003 for Maine only. The coefficient indicates that after 2003 the slope of the CMAD average cost line changed by $32.22 (per year) in Maine only. Since the absolute value of the t statistic associated with this coefficient (-0.136) is so small, the result is not statistically significant. It is the result of random variation. This means that the srHS model has not proven that cost increases over time in Maine after 2003 is different from Maine’s cost trend prior to 2003. This variable should be removed from the final model.

Q. Please summarize how these statistical significance results would affect your opinion on the validity of the srHS regression model in calculating cost savings?

A. In the U.S. hospital equation there are only two variables that can conceivably be used in an attempt to measure savings that may be correlated with the Dirigo variable. They are term tests for a reduction in the annual rate of increase in costs after FY 2003. The first term test, “MĐD” tests for a one time reduction in costs after 2003 (a vertical drop in the trend line). The second, “MĐDĐY” tests for a reduction in the annual rate of increase in costs after 2003 (a decrease in the slope of the trend line). The “Dirigo” or “D” binary variable tests for a one time reduction in costs for all U.S. hospitals after 2003, and the “MĐY” term tests for a higher annual trend in Maine costs prior to 2004.

Independent of the other problems with the analysis that I have identified in this testimony as well as those discovered by Dr. Dobson and Mr. Burke, the lack of statistical significance to test terms “MĐDĐY” and “MĐD” (the only variables in the srHS regression model that can conceivably correlate Dirigo savings) renders the model invalid for purposes of determining AMCS.

Q. Does that complete your testimony concerning the statistical insignificance of the srHS U.S. hospital regression model?

A. Yes. I will now move on to the point that the srHS model also failed to include factors that clearly affect hospital costs and should have been included as potential explanatory variables in the srHS U.S. model (and in models for any sample of states).

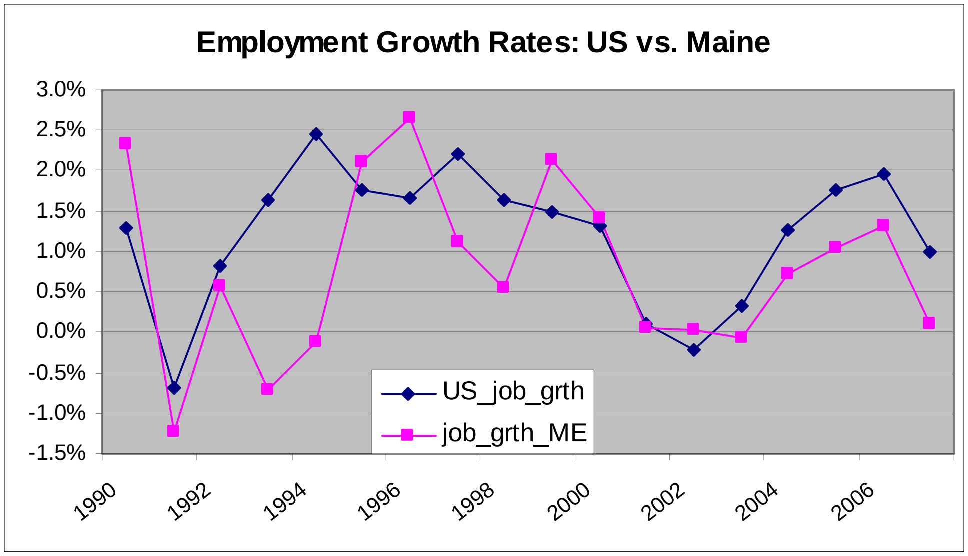
Q. Please describe the first factor that should have been included in the srHS analysis as a potential explanatory variable.

A. As a threshold matter, I would like to state that the dependent variable that srHS selected (cost per CMAD) is not appropriate to measure the cost savings from a cost of care intervention. This is dealt with more directly later in my testimony. Assuming, however, that cost per CMAD were an appropriate dependent variable, for the reasons discussed below, the first potential explanatory variables I would look to are economic variables such as employment growth rate. Inexplicably, srHS did not include state employment growth rate or similar economic drivers in its model.

Changes in economic factors are so powerful that they affect cost and output in every industry in the U.S. economy. Aggregate economic variables such as gross state product, unemployment rates and inflation should always be given serious consideration in any model using socio-economic data (especially economic data such as costs). For example, employment growth rates are powerful drivers of change in every industry, and especially so for the health care sector since the overwhelming majority of commercial subscribers receive their medical insurance through their employers. Changes in the level of employment will effect the percent of the population with medical insurance and thereby the level of medical spending. Since so much of the under 65 population gets its insurance through employers, as employment levels grow, so too do those who have insurance. In a growing economy, employers who offer insurance will hire more employees, some employers who had not previously offered insurance to their employees will be able to afford to do so, and, as per capita income grows, more employees will be able to afford their insurance co-shares, co-pays and deductibles. Not only does the number of insured lives increase, utilization rates for the insured increase as well. As a result, the growth in hospital revenues accelerates. As hospital revenues grow, the financial need for increases in reimbursement rates (*i.e.*, the average cost of a discharge or outpatient visit) eases. The growth in CMAD average cost should slow.

On the national level, by 2003, years of declining employment growth rates throughout the United States were contributing to the growing rates of uninsured, which in turn put downward pressure on hospital revenues and profit margins. These declining profit margins put pressure on hospitals to push for higher prices (*i.e.*, cost per discharge and cost per outpatient visit). When employment growth rates turned positive in 2004, the increase in the insured population resulting from the increase in employment allowed hospitals to ease up on their demands for higher per discharge/visit cost increases.

While a similar cycle occurred in Maine, the cost growth fluctuation was exacerbated because Maine experienced a much longer recession in employment growth (including 3 years of zero growth from 2001 to 2003) than the rest of the United States (see graph below). The length and depth of the recession in Maine would have put far more financial pressure on Maine hospitals to increase reimbursement rates (*i.e.*, cost growth) than it did on U.S. hospitals in general. When employment growth turned positive in 2004, the financial pressure on Maine's hospitals eased for the first time in three years.



The above graph reflects that the recovery in employment growth rates for the U.S. and especially for Maine is coincident with the phase change (from 1 to 0) for the 2004 "Dirigo" binary variable in the srHS models. Put differently, this means that employment growth in Maine was stagnant in the years that preceded 2004. Fewer jobs means fewer insureds and, hence, higher hospital cost growth. Starting in 2004, when employment growth in Maine accelerated, there were more jobs and more people covered by their employers' insurance, which in and of itself should lead to a deceleration of hospital cost growth. Since the employment growth factor is absent from the srHS model as a potential explanatory variable, the impact that positive and increasing employment growth has on growth of health care costs is likely to be improperly picked up by the 2004 "Dirigo" binary and/or any interaction term that is constructed using the 2004 "Dirigo" binary.

Q. What does it mean that the srHS model likely is picking up the impact of the post-2003 employment growth?

A. It means that the srHS estimated coefficients are biased. Put differently, independent of the statistical insignificance of the factors that are critical to the model (variables "MĐDĐY" and "MĐD"), the failure to include employment growth rates as a potential explanatory variable invalidates the statistical results of the srHS regression model because anticipated deceleration of cost growth associated with increased employment growth is included in the "savings" that the srHS model incorrectly attributes to Dirigo.

Since this shift from declining or zero employment growth to positive employment growth occurred exactly when the "Dirigo" binary variable changes phase in the srHS model, the "savings" that srHS attributes to Dirigo may, in large part, be due to changing economic fortunes. This is a more likely scenario given that economic factors have been consistently established in the research literature as powerful drivers of industry. The health care industry, at over 20% of GDP, is not exempt from those forces.

Q. Your explanation seems to suggest that hospital operating margins should have been considered as an additional explanatory variable in the srHS model. Is that correct?

A. Yes. Hospital operating margins will also have a significant effect on cost per case. Hospitals with slim or negative operating margins are under pressure to increase revenues and that leads to increased costs per case. By contrast, when hospital operating margins are more robust, the pressure to increase revenues is diminished and there is consequently less cost growth. Employment growth rates will have a strong influence on profit margins, but they are not the only factor operating on profit margins. Profit margins will have some movement that is independent of employment growth. As such, srHS should have (but did not) test hospital margin in the model along with employment growth rates. The graph provided by srHS shows that hospital operating margins in Maine improved in 2004 and after, which for the reasons stated above, eased the need for hospitals to increase their costs per case. Thus, even if srHS's model did not have any of the other deficiencies mentioned herein, the inclusion of employment growth rates and hospital profit margins would have dramatically changed their estimate of the Dirigo savings. Put differently, even aside from the other serious flaws in srHS's model, the fact that the srHS model does not control for two well-known factors generating hospital cost increases (*i.e.*, employment growth and operating margins) demonstrates that the model is fundamentally flawed and cannot be relied upon.

Q. In addition to the variables lacking statistical significance, you mentioned previously that there are problems with srHS's state cluster analysis. Please explain the problems with those clusters.

A. The Cluster 1 sample was not randomly selected. For starters, it is **unusually small** with only six states. Even though there are multiple hospitals within a state, they are all subject to the same state economic conditions and the same set of laws and regulations concerning health care and health care costs and operations. Changes in the economic conditions and regulatory environment will move the actual values for all hospitals in a specific state in a similar direction and by a similar magnitude. The resulting error terms (actual minus predicted) will move together in a similar fashion. They are not independent, and thus violate the basic ***iid*** assumption that underlies srHS's regression methodology. As a result, there is even more potential that the estimated coefficients are biased and that their statistical significance is lower than the calculated t statistics indicate.

Q. Did you find other problems with srHS's use of the Cluster 1 sample as a benchmark for Maine?

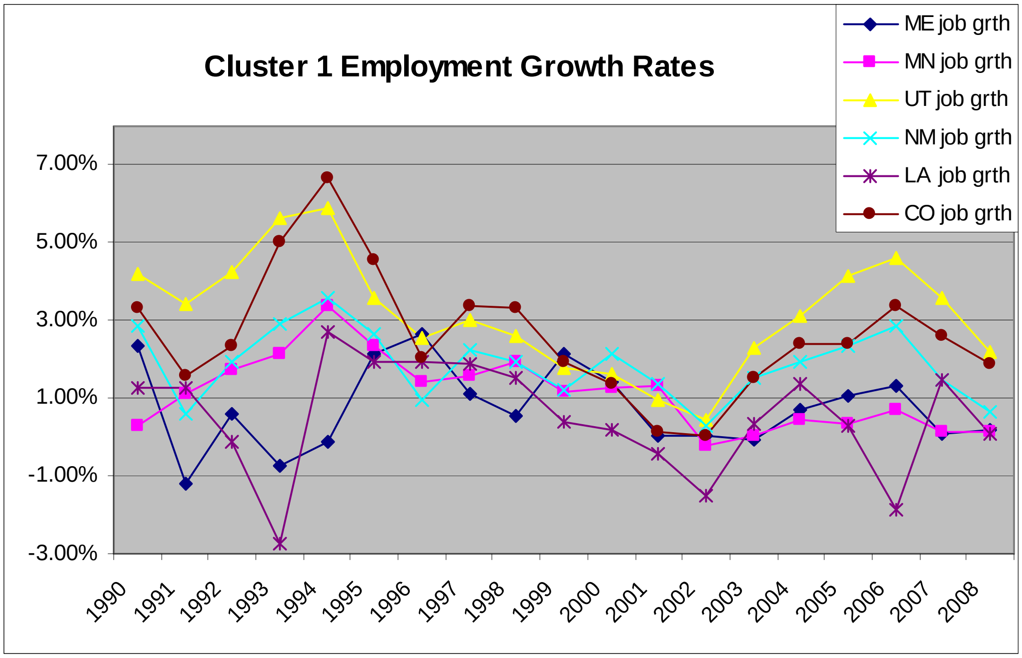
A. Yes, the states srHS selected have significantly disparate characteristics that make them inappropriate to create a valid benchmark for Maine. For example:

- The Cluster 1 sample includes Louisiana (LA) which had a double dip recession in employment growth rates due to hurricane Katrina (see graph below).
- Cluster 1 includes Utah (UT) which had nearly 2½ times the average job growth of the U.S., but was one of only a few states to have rising uninsured rates (an extraordinary 2½% point increase in the uninsured population from 2004 to 2007).
- Cluster 1 states Colorado (CO) and New Mexico (NM) had employment growth rates that were approximately three times that of Maine.

- This six state Cluster 1 sample includes three economically and sociologically related, adjacent states in the Southwest (CO, NW, UT). That is highly unusual, especially when compared to Maine, a state in the Northeast.

- The ethnic make-up of the Cluster 1 states also renders the sample inappropriate. According to the U.S. Census Bureau, in 2004, Maine was 96% White/Caucasian and less than 1% each for Black and Latino. MN was the closest at 87% White, 4% Black and 3% Latino. Race differences start to become pronounced in UT, with a sizeable Latino population at 10%, a White population representing 84%, and a Black population of only 1%. In CO, the minority difference with Maine becomes even more dramatic: CO is 19% Latino, 73% White, and 4% Black. In LA, the dominate minority is the Black population at a sizable 33% (compare to Maine's less than 1%), with the White population accounting for 62% and the Latino population for 3%. In NM, the "minority" population outnumbers the White/Caucasian population. NM is only 44% White (compared to Maine's 96%), 43% Latino, and 2% Black. There are significant ethnic differences between Maine and Cluster 1 states UT and CO. The differences become dramatic when we compare Maine to LA and NM. Given that there are dramatic differences nationally in insurance rates for different ethnic groups (*i.e.*, White/Caucasian compared to Back or Latino), Cluster 1 is not a good benchmark for Maine.

- There are also large differences in age among the Cluster 1 sample states. Again, according to the U,S. Census Bureau, in 2005, the median age in Maine was 41 years. MN and NM were the closest with median ages of 36 and 36½ respectively, but in terms of population dynamics, that difference is very significant. Age differences are even greater when we look at CO and LA at 35 each. With an average of 28, UT cannot be compared to Maine. Given that there are dramatic differences in insurance rates of different age groups, Cluster 1 is not a good benchmark for Maine.



Q. Do these differences render Cluster 1 an invalid sample?

A. Yes. Among other things, having such a large portion of a small sample concentrated in one small geographic region of the country, with similar socio-economic conditions that are dramatically different from Maine, does not make for a valid benchmark.

What is important about the differences discussed above is that the response of Maine to changing socio-economic factors will be different from the other states in Cluster 1 because of dramatic differences in employment growth, age and race. Insurance rates among minorities are much lower than they are for White/Caucasian populations. Additionally, insurance rates among younger age groups are much lower than they are for the older groupings. Socio-economic events that would tend to decrease uninsured rates will have a smaller effect in states with greater concentrations of minorities and/or younger populations than they will in Maine. This makes it almost impossible to determine what role, if any, Dirigo played in cost growth using Cluster 1.

Q. Did you note other problems that call into question the validity of Cluster 1?

A. Yes. As reflected in the table below, Cluster 1 was the only one of four samples (Cluster 1, Cluster 2, a grouping of states compiled by the Brookings Institute for comparison purposes for the state of Maine, and the New England states) where the percentage of insured actually increased from 2004 to 2007. Cluster 2's percent insured <u>decreased</u> by 0.7% points (0.8% points without Maine in the calculations). The Brookings cluster percentage insured <u>decreased</u> by 0.4% points (with or without Maine in the calculations). The New England states experienced a 0.4% point <u>decrease</u> in the percent uninsured (0.2% points without Maine in the calculations). Cluster 1's percent insured **<u>increased</u>** by 0.2% points (0.4% points without Maine in the calculations).

Further, like in the U.S. hospital analysis, the two variables critical to testing for Dirigo correlated savings ("M**Đ**D**Đ**Y" and "M**Đ**D") in Cluster 1 are not statistically significant. That the "M**Đ**D**Đ**Y" test term comes close to achieving statistical significance (the t statistic's absolute value of 1.6413 nears the critical t value of 1.645) is not surprising. What the coefficient for the "M**Đ**D**Đ**Y" interaction may be telling us is that people in Maine had a different health care/insurance related response to socio-economic changes in 2004 than people in the other states of Cluster 1. This is exactly what we would have expected given the dramatic age and ethnic differences between Maine and the rest of Cluster 1. Put differently, because srHS used a cluster of states that are dramatically different in several basic characteristics that would inherently produce different cost per CMAD results, any correlative value resulting from this flawed cluster is simply invalid as it is merely picking up those fundamental differences among these states.

US Census Bureau: **2005 to 2007** Annual Social & Economic Supplements							
% Uninsured		**% Uninsured**		**% Uninsured**		**% Uninsured**	
Cluster 1	%	Cluster 2	%	Brookings	%	New England-ME	%
Colorado	16.5%	Hawaii	9.0%	Vermont	11.0%	Vermont	11.0%
Louisiana	18.5%	Idaho	15.0%	Michigan	10.5%	New Hampshire	10.5%
Minnesota	8.5%	Nebraska	11.0%	Wyoming	14.0%	Rhode Island	10.0%
New Mexico	21.0%	New Hampshire	10.5%	South Dakota	11.5%	Connecticut	10.5%
Utah	16.0%	New Mexico	21.0%	North Dakota	11.0%	Massachusetts	10.5%
Maine	9.5%	Rhode Island	10.0%	Montana	17.0%	Maine	9.5%
simple Avg	15.0%	West Virginia	15.5%	West Virginia	15.5%	simple Avg	10.3%
		Maine	9.5%	Arkansas	17.5%		
Avg w/o Maine	16.1%	simple Avg	12.7%	Iowa	9.5%	Avg w/o Maine	10.5%
				New Hampshire	10.5%		
		Avg w/o Maine	13.1%	Maine	9.5%		
				simple Avg	12.5%		
				Avg w/o Maine	12.8%		

US Census Bureau: Income, Poverty, and Health Insurance Coverage in the US: **2004**							
% Uninsured		**% Uninsured**		**% Uninsured**		**% Uninsured**	
Cluster 1	%	Cluster 2	%	Brookings	%	New England-ME	%
Colorado	16.5%	Hawaii	10.0%	Vermont	10.5%	Vermont	10.5%
Louisiana	19.0%	Idaho	17.5%	Michigan	11.5%	New Hampshire	10.5%
Minnesota	8.0%	Nebraska	11.0%	Wyoming	15.0%	Rhode Island	10.5%
New Mexico	21.5%	New Hampshire	10.5%	South Dakota	12.0%	Connecticut	11.0%
Utah	13.5%	New Mexico	21.5%	North Dakota	11.5%	Massachusetts	11.0%
Maine	10.5%	Rhode Island	10.5%	Montana	18.0%	Maine	10.5%
simple Avg	14.8%	West Virginia	16.0%	West Virginia	16.0%	simple Avg	10.7%
		Maine	10.5%	Arkansas	16.5%		
Avg w/o Maine	15.7%	simple Avg	13.4%	Iowa	10.0%	Avg w/o Maine	10.7%
				New Hampshire	10.5%		
		Avg w/o Maine	13.9%	Maine	10.5%		
				simple Avg	12.9%		
				Avg w/o Maine	13.2%		

In summary, Cluster 1 does not provide a valid benchmark for Maine. Among other data points, LA with its double dip jobs recession and UT with an employment growth rate of 2½ times the national average but with a 2½% point increase in the uninsured point likely had a significant impact on the sample. Further, CO and NM have so much in common with UT that they polarize the sample. Simply put, Cluster 1 is not an appropriate benchmark for Maine.

Q. What does the srHS model suggest for CMAD savings?

A. The srHS model calculates $147.9 million in CMAD savings.

Q. Based on your review of the srHS model, is that calculation an accurate reflection of the amount of cost savings that are attributable to Dirigo?

A. The answer is no. The statistically insignificant coefficients for the "MĐD" and "MĐYĐD" terms which are critical to the hypothesis that Dirigo changed (*i.e.*, reduced) CMAD costs in Maine should not be used to calculate savings correlated to Dirigo. In addition, even if the results that are critical to srHS's model were statistically significant (which they are not) srHs's violation of the fundamental iid requirement means that the calculated t statistics may be biased upwards, which calls into question the statistical significance of all coefficients.

Further, the use of the coefficients from the Cluster 1 regression when Cluster 1 was not a randomly selected sample, and thus inappropriate and unreasonable to use for a Maine benchmark/comparison group, clearly biases the "savings" calculation upwards.

In short, srHS's use of a badly mis-specified model invalidates all their results. The model is mis-specified because it fails to include the all-important economic and hospital financial variables in their proper mathematical form with appropriate lags.

Q. In addition to numerous other flaws, Dr. Dobson noted that the dependent variable (cost per CMAD) should have been logged. Do you agree?

A. Yes. Proper mathematical formulation would be the log of the dependent variable. Historically, U.S. health care costs have exhibited a constant rate of growth. "Log linear" estimation will return a constant rate of growth. If one runs regressions on the original dollar measures of cost, as srHS has done, it will return costs that grow at a constant dollar amount. If costs are growing at a constant dollar amount each year, then the rate of growth (the constant $ increase divided by an ever growing prior period $ amount) will decrease each year. If you then calculate rates of growth based on values predicted by the equation you will get declining rates of growth that are the result of basic mathematics, even if there were no "real" decline in the growth of costs.

Q. Are there other indicia that suggest that the srHS model was mis-specified?

A. Yes. Model mis-specification is further indicated by the presence of different variables in the U.S. hospital and Cluster 1 equations, and the instability of the coefficients of the variables that are common to both equations. Consider that the "Rural Indicator", "Interns per Bed", and the measure of "Uninsured" are in the U.S. Hospital equation but not the Cluster 1 equation. The "Critical Access Indicator" and the "% Medicaid Days" are in the Cluster 1 equation but not the U.S. hospital equation. The coefficient for "Total Beds" experiences an eight-fold increase from 0.1095 in Cluster 1 to 0.8724 in the U.S. hospital data set. The "% Medicare Days" shrink by 80% from -6611 in Cluster 1 to -1332 in U.S. hospital. A robust, well-specified model should work reasonably well regardless of the sample chosen. If the coefficients and variables are inconsistent (as they are in the srHS model), that is an indication of a badly specified model.

All of the above points lead me to conclude that the srHS results are invalid and cannot be relied upon. Undoubtedly, some of the factors identified in the srHS study may be correlated to CMAD costs. However, the lack of a complete model and the biases introduced prevent us from knowing how much of a savings, if any, has been generated by Dirigo.

Q. Your testimony indicates that both the U.S. hospital analysis and the Cluster 1 analysis employed by srHS were statistically unsound?

A. Yes, for the reasons described above, both analyses are fatally flawed.

Q. Mr. Schramm seems to concede in his prefiled testimony that neither the U.S. hospital analysis nor the Cluster 1 analysis can produce results that accurately predict savings that are correlated to Dirigo on its own, but suggests that blending

the two cures the flaws. Does this suggestion—that blending the results from two faulty models together can create new results with stronger predictive and explanatory power –make sense from a statistical and econometric standpoint?

A. No. The blending of results from two different models is highly unusual. If a researcher has a properly specified model, the results from the larger sample should be used as smaller samples are more prone to biased results. "Blending" two regressions that are mis-specified cannot correct the flaws that are inherent to each regression. The science of statistics does not stray from the maxim "two wrongs do not make a right." Generally speaking, two faulty data sets fused together do not somehow produce a statistically valid result.

Q. Mr. Schramm suggests that the U.S. regression has predictive value (though admitting a lack of statistical significance) and that Cluster 1 (though a small and potentially biased sample) has explanatory value. Do you agree?

A. No. The U.S. hospital analysis and the Cluster 1 analysis are not data sets where one corrects the flaws in the other, thereby making the blended results stronger than the initial outputs. To the contrary, even it were appropriate statistical technique to blend two analyses in an attempt to correct deficiencies (which it is not) rather than offsetting opposite deficiencies, the two analyses are embedded with the same flaws. As explained above, both the U.S. hospital analysis and the Cluster 1 analysis failed to remove variables that demonstrate no statistical significance, including the ony variables in the srHS regression model that can conceivably measure Dirigo savings ("MĐDĐY" and "MĐD"). Further, both models failed to include economic and financial variables that are important drivers of health care costs--variables such as employment growth and hospital operating margin, thereby invalidating the estimates for the coefficients of the included variables. Simply put, the results srHS produced from blending and weighting the U.S. hospital analysis and the Cluster 1 analysis are no more explanatory or predictive than the fundamentally flawed results those two models exhibited on their own.

Q. Even if the srHS model properly measured declines in cost growth that are actually attributable to Dirigo, in your opinion as a statistician and health economics expert, is a system wide analysis of changes in CMAD an appropriate mechanism to determine true cost growth declines?

A. No. The use of CMAD formula to measure the cost containment performance of **individual hospitals** may indeed be appropriate. Even though the admit rate and the mix of cases should be stable for an entire health care system such as the state of Maine, random variation and competition among hospitals will cause both the number of admits and case mix at individual hospitals to vary. Hospitals should not be penalized if healthy competition for physician and patients generates an increase in admits or a shift in the mix of cases towards more resource intensive (and costly) admits. Nor should they be rewarded if the mix of cases at their institution shifts towards less resource intensive (lower cost) admits.

However, what is appropriate at the individual level may not be appropriate for an entire system. Any measure of statewide medical cost control should consider changes in total medical cost. The CMAD formula only considers one component in the total cost equation, the price (*i.e.*, the case mix adjusted average cost) of a discharge. The srHS approach then takes the change in the cost of an admit and multiplies by the current number of discharges. Normally, an increase in the statewide admit rate would be viewed as an indication of possible overuse of acute care facilities (*i.e.*, waste). However, using the srHS approach, any increase in admits is interpreted as an increase in savings as long as the case mix adjusted ("CMA") cost has declined.

An increase in admit rates may even lower CMAD costs. Since hospitals have huge fixed costs in physical plant and equipment, an increase in admits and out patient visits allows the hospital to spread their fixed costs over a larger patient base, thereby reducing average cost. Additionally, when admit rates go up, more often than not it is because cases at the margin are now being admitted. Marginal cases are the ones where the patient's condition may or may not require admission to an acute care hospital. These patients are not quite as serious and not quite as expensive to treat as the clear cut cases. Yet the diagnosis codes and procedures done will be similar, yielding similar Case Mix Index ("CMI") values but similar or lower costs than those clear cut admits. If more marginal cases are being admitted, then there is a strong presumption that acute care facilities are being inappropriately utilized. However, the CMI may stay the same and the CMAD cost may fall. Even where there is some cost savings from improved efficiency the CMAD formula will overstate those 'saving' by multiplying by an admit rate which can be inflated by inappropriate/excessive hospitals admits.

Q. Dr. Dobson's analysis reflects that the srHS model will calculate "savings" correlated to Dirigo in many other states that are not subject to the Dirigo Health legislation. As a statistician and econometrician, are you surprised by this?

A. No. The statistical insignificance of the results from the srHS model means that random variation can result in a "savings" calculation and, as such, "savings" can be generated in any state. Additionally, the exclusion of important explanatory variables, such as employment growth and operating margin, can likewise generate such "unusual" results. Use of an inappropriate cluster as a benchmark further undermines the srHS model. LA had the "double dip" employment growth recession, UT had that unusual 2½% increase in uninsured rates, and CO, NM and UT had emplyment growth rate 1½ to 2½ times greater than national rate. The use of such an unusual benchmark is bound to result in "savings" for states similar to Maine.

Q. Why is this not surprising given that those other states do not have Dirigo?

A. In the first instance, the srHS model suggests that they attempted to measure the effects of "Dirigo", but as I noted above, the variable labeled "Dirigo" and the interaction created using the "Dirigo" binary variable in the srHS model are not "Dirigo" at all. Rather, those variables simply partition the data between two time periods; ***i.e.***, the time period before FY 2004 and the time period including and after FY 2004. Instead of actually measuring declines in cost growth that are correlated to Dirigo, the srHS model measures declines after 2004 and assumes that if cost growth slows more in the target state than the benchmark, not only is it potentially correlated to Dirigo, it is actually attributable to Dirigo. As I testified above, the mis-specification of the model by failing to control for employment growth and hospital operating margin changes (and other potential economic and hospital specific financial factors) is one of the most serious flaws in the srHS model. The srHS model is not in reality measuring cost growth decline that is correlated to Dirigo, but instead is simply measuring variations in the rate of cost growth across different states. Because of different economic, sociological, and regulatory conditions, there will be different rates of cost growth, both before and after 2004, among the states. This will be especially true for the state of Maine which experience a longer and deeper economic pre-Dirigo recession than the rest of the country.

Q. In his testimony Dr. Dobson suggests that the srHS model should have included additional dependent variables beyond employment growth and operating margin. Do you have any comment on this?

A. Yes. Many of Dr. Dobson's variables are simply "component" variables that determine hospital profits. "HMO penetration", "Profit/Non-Profit Hospital Status", "Occupancy Rates" and other components all influence hospital profits. I suggested "hospital profit / operating margins" as a variable that would easily capture the combined effect of Dr. Dobson's components. Dr Dobson also suggests "Income Levels and Wages" which fit the general category of "economic and employment growth" factors that I suggested. Additionally, Dr Dobson suggests "Race" and "Age" which figured prominently in my critique of Cluster 1. As such, our views of the variables that were improperly omitted from the srHS model are entirely consistent.

Q. Do you have any comments on the other savings measures proposed by srHS?

A. Yes. Since the turn around in employment growth is correlated with the reduction in the CMAD growth rate, and since the major logical link is through emplyment growth's tendency to increase growth in uninsured rates (all other factors held the same), then this strongly suggests that savings associated with reductions in bad debt and charity care are already included in the CMAD measure. Put differently, if employment growth accelerates and creates jobs, this leads to an increase in those with commercial insurance, which will tend to reduce the cost per CMAD. As such, including the reduction in the uninsured rates as a separate measure of savings is double counting.

Q. Mr. Schramm suggests in his testimony that there is no overlap because their calculation analyzes costs in both the pre- and post-Dirigo periods and determines the BC/CC savings independent of those cost changes. Do you agree?

A. No. The strong link between employment growth rates and uninsured rates combined with the reversal of employment growth rates after Dirigo (*i.e.*, in 2004) suggest otherwise.

Q. Does this conclude your testimony?

A. Yes.

Certificate of Service

I, Christopher T. Roach, Esq. certify that the foregoing Prefiled Testimony of Vincent Maffei was served this day upon the following parties via Electronic Mail.

Dirigo Health Agency
Attn: Ruth Ann Burke
211 Water Street
Augusta, Maine 04333-0053

William Laubenstein, Esquire
Office of the Attorney General
6 State House Station
Augusta, ME 04333-0006

Michael Colleran, Esquire
Office of the Attorney General
6 State House Station
Augusta, ME 04333-0006

William Stiles, Esquire
Verrill Dana LLP
One Portland Square
P.O. Box 586
Portland, ME 04112-0586

Bruce Gerrity, Esquire
Preti, Flaherty, Beliveau, Pachios & Haley LLP
45 Memorial Circle
P.O. Box 1058
Augusta, ME 04332-1058

D. Michael Frink, Esquire
Curtis Thaxter Stevens Broder & Micoleau LLC
One Canal Plaza
P.O. Box 7320
Portland, ME 04112-7320

Mia Poliquin Pross, Esquire
Consumers for Affordable Healthcare
P.O. Box 2490
Augusta, ME 04338-2490

Dated: July 9, 2008

/s/ Christopher T. Roach
Christopher T. Roach, Esq.
Lucus A. Ritchie, Esq.

PIERCE ATWOOD, LLP
One Monument Square
Portland, ME 04101

(207) 791-1100
Attorneys for Intervenor
Anthem Health Plans of Maine, Inc.