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EVALUATING DISEASE MANAGEMENT PROGRAM EFFECTIVENESS ADJUSTING FOR ENROLLMENT (TENURE) AND SEASONALITY

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ABSTRACT

This paper introduces the concept of regression analysis to emulate the key characteristics of two statistical methods having properties uniquely suited for disease management program evaluation; survival analysis and its ability to adjust for the impact of length of program enrollment, and time-series analysis and its ability to adjust for seasonality. The simulated data created for this paper are meant to replicate a disease management program over the course of two years, serving a total of 1000 members, who enrolled and disenrolled at various points throughout the program. The outcome variable chosen was hospitalizations. These data were intentionally designed to include a seasonal component as well as a reduction in the program effect over time. A detailed explanation of the regression model development and use of its resulting output is discussed.

Disease management (DM) programs were developed under the assumption that health services utilization and morbidity could be reduced for those with chronic illness by augmenting the traditional episodic medical care system with services and support between doctor visits. For many chronic diseases, there is much opportunity to improve the quality and consistency of care (*e.g.* diabetics getting regular tests of glucose control (HbA1c) or those with known coronary disease taking a beta blocker). DM programs were developed to assist physicians and their patients to identify and close those gaps in care (DMAA, 2004).

DM programs attempt to achieve these goals by (1) accurately identifying those in the population with the disease or at significant risk of developing the disease, (2)

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convincing those with the greatest risk of morbidity and health services utilization to participate in the program and (3) intervening with physicians and patients to effect some change in health behavior. For many DM programs, the primary means to execute these intervention strategies is through telephonic interaction between a DM nurse, the patient and physician. According to the Disease Management Association of America (DMAA), a full-service disease management program must include all of the following: population identification processes, evidence-based practice guidelines, collaborative practice models to include physician and support-service providers, patient self-management education, process and outcomes measurement, evaluation and management, and routine reporting/feedback loops (which may include communication with patient, physician, health plan and ancillary providers, and practice profiling) (DMAA, 2004).

Although DM has been in existence for over a decade, there is still much uncertainty as to its effectiveness in improving health status and reducing costs. Part of the struggle to gain legitimacy is the ambiguity in how to best evaluate DM program effectiveness. Several research-based techniques with applicability to DM have recently been introduced to the DM evaluation debate (Linden, Adams & Roberts, 2003a, 2003b, 2003c, 2004a, 2004b, 2004c, 2004d, 2004e; Linden & Roberts, 2004; Linden, Roberts & Keck, 2003).

A prevailing theme in these papers is that many research-based techniques can be applied to the evaluation of DM programs, with each technique typically having at least one particular characteristic that makes it more suitable than others for a given evaluation problem. For example, the propensity scoring technique uses logistic regression to create a single independent variable representing the participant's entire set of covariates, making it feasible to match program participants and controls on the one variable instead of several (Linden, Adams & Roberts, 2004d). Bootstrapping (Linden, Adams & Roberts, 2004e) offers the ability to develop standard errors (SE) and confidence intervals (CI) around quantities that the classical statistical tools do not provide for (*e.g.* median, percentiles, non-linear functions, etc). Survival analysis (Linden, Adams & Roberts, 2004c) allows for the inclusion of data from censored cases, those subjects who either "survived" the program without experiencing the event (achievement of target clinical levels, hospitalization, *etc.*) or left the program prematurely, due to disenrollement from the health plan or program, or were lost to follow-up. Similarly, time-series analysis (Linden, Adams & Roberts, 2004c) allows for the observation of the outcome variable over time to determine the program effect despite the presence of trend and/or seasonality.

This paper introduces the concept of regression analysis to emulate the key characteristics of two previously discussed methods; survival analysis and its ability to adjust for the impact of length of program enrollment, and time-series analysis and its ability to adjust for seasonality. The simulated data created for this paper are meant to replicate a DM program over the course of two years, serving a total of 1000 members, who enrolled and disenrolled at various points throughout the program. The outcome variable chosen was hospitalizations. These data were intentionally designed to include a seasonal component as well as a reduction in the program effect over time.

PROGRAM TENURE

Adjusting for a participant's period of enrollment in the program ("tenure") has been an unresolved issue in the evaluation of a program's effectiveness. The most typical method of adjustment for tenure is by summing the total number of months that all program eligible individuals were enrolled at the health plan or in the program. This value, typically called "member-months" is then used as the denominator, while the outcome variable is used in the numerator (*e.g.* count of hospitalizations, office visits, *etc.*). However, by aggregating, how the length of time in the program will impact the individual participant's outcome is left unresolved. In other words, can hospitalizations be expected to decrease with increased exposure to the program intervention, and if so, when?

Another method sometimes employed in program evaluation to maximize the potential for identifying a positive intervention effect is to include only those members who were continuously enrolled long enough to be influenced by the program intervention (typically 12 months). However, by eliminating participants from the evaluation who were enrolled in the program for shorter periods of time, we are eliminating their contribution to developing an informative evaluation model.

SEASONALITY

Another concern, typically not addressed in DM, is the possible existence of seasonality. Seasonality is a pattern at regular intervals in a time series (usually monthly, quarterly or annually). This effect has been well documented to exist for certain illnesses (such as ED visits for the flu, allergies, asthma, *etc.*), as well as in the older population which typically shows a seasonal spike in hospital admissions around December and January (Linden, 1997; Linden & Schweitzer, 2001).

If seasonality is unaccounted for, patterns at regular intervals may; (a) skew the program results, especially if the evaluation period is less than one year and (b) act as a potential source of confounding with program tenure. For example, let's assume a DM program targeting Medicare members begins implementation and enrollment in January, and is then evaluated in the following January. Without adjusting for seasonality, we may interpret the large number of hospitalizations at the beginning of the program as a good indicator that the identification algorithm properly identified the sickest patients, but that the program was not capable in so short a period to impact those admissions. However, the spike in hospitalizations in the following December/January may be misinterpreted as a failing of the program to impact hospitalizations for an extended period of time.

REGRESSION ANALYSIS

Regression is a statistical technique that uses one or more explanatory variables to help identify a relationship with the outcome variable. In DM, regression is typically used in area of "predictive modeling." (Cousins, Shickle & Bander, 2002). A predictive model usually entails identifying several demographic and disease related factors (covariates) to estimate the cost or level of health service use that a given patient is predicted to accrue in the following year. With this information, a DM company can determine which members are most suitable for immediate program enrollment.

Regression may be used to predict (a) an outcome that occurs during the same period that the explanatory variables are measured, which is referred to as *concurrent regression*, (b) a future outcome, which is referred to as *predictive regression*, or (c) variables over time, which is referred to as *time-series regression*. The predictive model example given earlier is an illustration of a predictive regression to forecast next year's costs. The focus of this paper will be time-series regression, since both the explanatory variables (program tenure and the month of the year) and the outcome variable (hospitalization rate) are time-dependent.

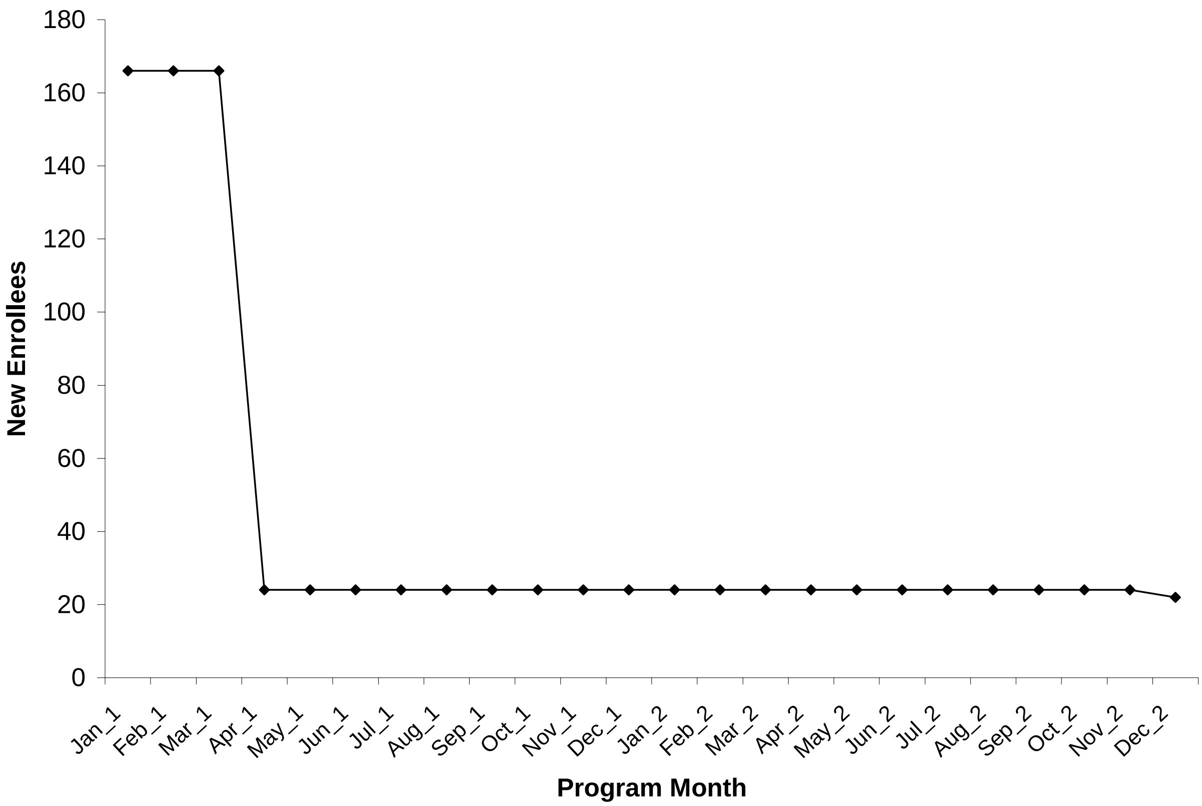
Time series regression like any other form of time series analysis is based on the premise that the outcome variable under observation is to some degree influenced by previous observations (autocorrelation). Whereas other time series models use past observations as the covariates for predicting future outcomes, regression allows us to include other time-dependent variables to help explain the variation in the outcome variable. In the model presented here, for example, two sets of time-dependent covariates are used - the month of tenure that a participant is in the program, and the month-of-year. Similarly, the effect of an intervention can be tested using this method by creating a variable indicating in which month the intervention was introduced. Of course, the assumption here would be that the intervention would have an immediate effect that would coincide with the date of implementation. For the purpose of our model development, the regression equation is used only for its form and function and thus, is not subject to the typical methods used for specification, estimation, and examination of goodness of fit.

DESIGNING A MODEL TO ADJUST FOR PROGRAM TENURE AND SEASONALITY

In this section, the steps taken to building a time series regression model that adjusts for the tenure and seasonality will be introduced. As mentioned earlier, the regression model developed in this paper was based on a hypothetical data set that was created to simulate an actual DM program's experience over the course of a two-year period. To make the example more meaningful to the reader, the effects of seasonality and program tenure were accentuated. As shown in Exhibit 1, 1000 members were enrolled in the simulated program over the course of a 24-month period. The first 3-month period (January–March of year 1) was intended to replicate a typical initial DM enrollment drive in which the identified suitable population is distributed into 3 evenly divided cohorts and contacted at monthly increments. After the initial bulk enrollment is completed, small numbers of new members were identified and contacted monthly. While the total number of members that enrolled in this simulated DM program was 1000, members were enrolled for different lengths of time.

Exhibit 2 illustrates the simulated hospitalization rate per thousand members by program tenure and month-of-year. For tenure, hospitalization rates were high in the first month of the program then fluctuated at a lower level until month 21 at which point a steady rise continues until the 24th month. We can hypothesize that the initial spike in admissions is due to the accuracy of the patient identification process, in which the highest-risk members are enrolled first. Because of their illness severity, these members tend to experience hospitalizations at a greater rate up-front. The long period of lowered admission rates throughout the program may be due to the increasing influence of the intervention or an effect of regression to the mean. We can also posit that the program begins to have a diminished effect at month 21 until the end of the program year 2.

EXHIBIT 1
NEW MONTHLY ENROLLMENT FOR A SIMULATED DISEASE MANAGEMENT PROGRAM

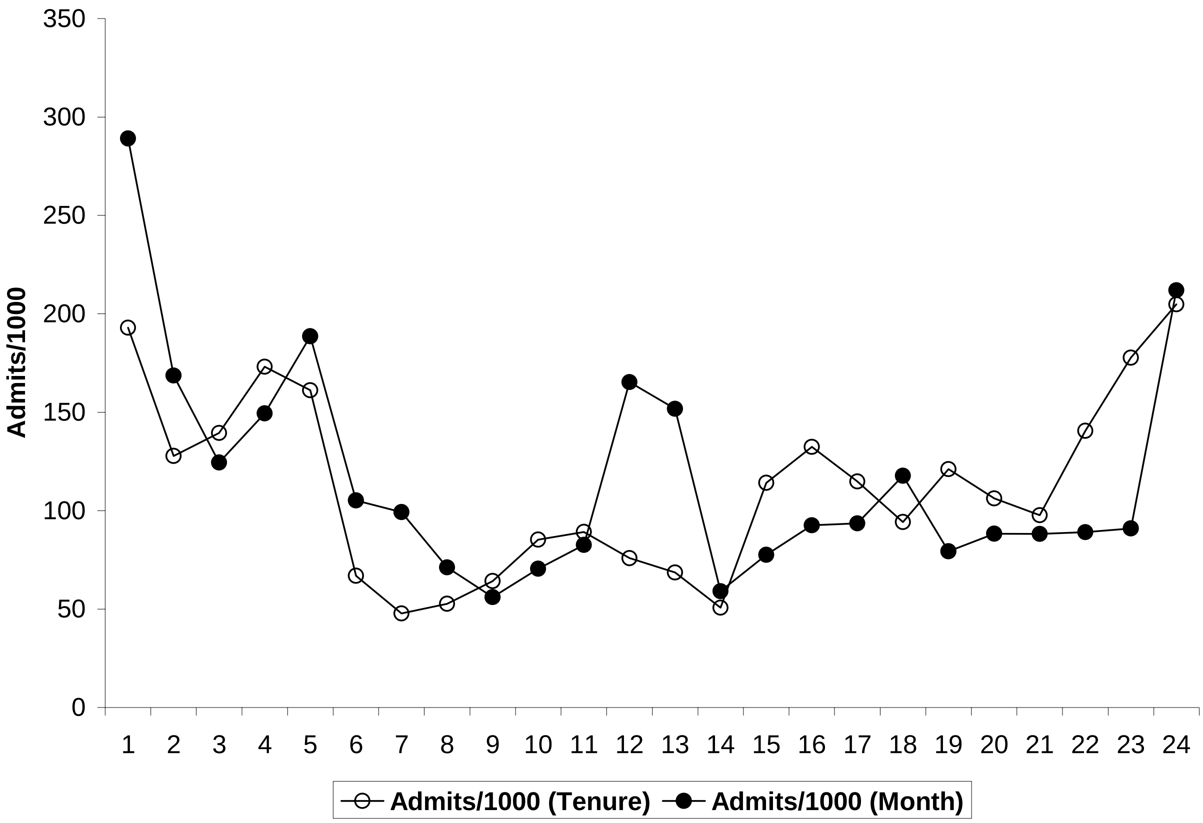


The first three months were intended to replicate a large initial enrollment drive, based on claims identified members.

As illustrated in Exhibit 2, the admission rate by month of the year follows a similar trend to that of tenure, however a spike appears at months 12 and 13 (December and January) whereas there is none for tenure during those same months. This is a clear case of seasonality, which appears as annual spikes in December and January.

This example provides a good illustration of why it is important to (a) visually inspect time series plots of important variables to see if observable patterns in the data emerge, and (b) to adjust for seasonality, especially in cases where program initiation coincides with a known seasonal spike in the outcome variable. Without overlaying the month-of-year admission series over the tenure series it would be easy to misinterpret the tenure data. However, with both sets of information the spike in the first and last month of tenure may be viewed as a result of seasonality, or a possible interaction between tenure and seasonality.

EXHIBIT 2
SIMULATED HOSPITAL ADMISSIONS PER THOUSAND MEMBERS



Based on program tenure and month-of-year (months 1–12 represent Jan.–Dec. of program year 1, and months 13–24 represent Jan.–Dec. of program year 2).

In the present regression model, the method used to represent seasonality and tenure is to create a set of dummy variables for each component. Exhibit 3 shows how this is task is carried-out. The first line of data in the Exhibit 3 indicates that Person 1 enrolled in the program of January of the 1st program year (Month = 1, tenure = 1). All dummy variables for both tenure and month-of-year, are set to 0. The reason for this is that a dummy variable is dichotomous, carrying a value of either 0 or 1. As such, Ten2 = 1 if tenure is the 2nd month of tenure, and Ten2 = 0 if it is not the 2nd month. When all tenure variables are set to 0, the default value for the set = the 1st month of tenure. The same is true for the month-of-year variable. Mon2 = 1 if the month is February, else 0 if it is not February. When all month-of-year dummy variables are set to 0, the default value for that line of data = January. This case in point is illustrated in the second line of data for person 1. As shown, person 1 was enrolled for month 2 of the program, which coincided with February as the month of the year (Ten2 = 1, and Mon2 = 1). Person 2 is shown in Exhibit 3 to have enrolled in the program in October of program year 2, and was enrolled for only 3 months. In that last month (December of program year 2), the individual was hospitalized.

Exhibit 3

SAMPLE DATA FROM THE SIMULATED DATA SET
SHOWING THE USE OF DUMMY VARIABLES TO HANDLE TENURE AND SEASONALITY

Person	*Month*	*Tenure*	*Admit*	*Ten2*	*Ten3*	*Ten4*	...	*Ten22*	*Ten23*	*Ten24*	*Mon2*	*Mon3*	*Mon4*	...	*Mon22*	*Mon23*	*Mon24*
1	1	1	0	0	0	0		0	0	0	0	0	0		0	0	0
1	2	2	0	1	0	0		0	0	0	1	0	0		0	0	0
1	3	3	0	0	1	0		0	0	0	0	1	0		0	0	0
1	4	4	0	0	0	1		0	0	0	0	0	1		0	0	0
1	22	22	0	0	0	0		1	0	0	0	0	0		1	0	0
1	23	23	0	0	0	0		0	1	0	0	0	0		0	1	0
1	24	24	1	0	0	0		0	0	1	0	0	0		0	0	1
2	22	1	0	0	0	0		0	0	0	0	0	0		1	0	0
2	23	2	0	1	0	0		0	0	0	0	0	0		0	1	0
2	24	3	1	0	1	0		0	0	0	0	0	0		0	0	1

Ten2–Ten24 are dummy variables representing month of tenure, and Mon2–Mon24 are dummy variables representing month of the year (January of year 1 through December of year 2). The breaks in the data between Ten4 and Ten22, and between Mon4 and Mon22 are due to space limitations in this Exhibit only. For the purpose of model construction, all 22 dummy variables are included as explanatory variables.

Upon completion of formatting the data set in the manner presented in Exhibit 3, a linear regression equation can be applied using any commercially available software product (Microsoft Excel offers regression in its data analysis pack, however, it is limited in the number of variables it can accept). Following equation (2) using this simulated data-set we arrived at the following formula:

$$\text{Hospitalizations} = 0.289 - 0.0466(\text{Ten2}) - 0.0367(\text{Ten3}) - 0.0021(\text{Ten4}) - 0.0126(\text{Ten5}) - 0.0994(\text{Ten6}) - 0.121(\text{Ten7}) - 0.115(\text{Ten8}) - 0.106(\text{Ten9}) - 0.106(\text{Ten10}) - 0.120(\text{Ten11}) - 0.132(\text{Ten12}) - 0.116(\text{Ten13}) - 0.112(\text{Ten14}) - 0.0465(\text{Ten15}) - 0.0312(\text{Ten16}) - 0.0433(\text{Ten17}) - 0.0634(\text{Ten18}) - 0.0277(\text{Ten19}) - 0.0460(\text{Ten20}) - 0.0553(\text{Ten21}) - 0.0487(\text{Ten22}) - 0.0317(\text{Ten23}) - 0.0660(\text{Ten24}) - 0.0972(\text{Mo2}) - 0.137\ (\text{Mo3}) - 0.113(\text{Mo4}) - 0.0828(\text{Mo5}) - 0.147(\text{Mo6}) - 0.121(\text{Mo7}) - 0.124(\text{Mo8}) - 0.137(\text{Mo9}) - 0.126(\text{Mo10}) - 0.112(\text{Mo11}) - 0.0226(\text{Mo12}) - 0.0337(\text{Mo13}) - 0.128(\text{Mo14}) - 0.126(\text{Mo15}) - 0.128(\text{Mo16}) - 0.139(\text{Mo17}) - 0.112(\text{Mo18}) - 0.152(\text{Mo19}) - 0.143(\text{Mo20}) - 0.144(\text{Mo21}) - 0.140(\text{Mo22}) - 0.141(\text{Mo23}) - 0.0183(\text{Mo24}).$$

This regression formula provides a predicted value for the number of hospitalizations that a given member is expected to experience based on the month tenure in the program and month-of-the-year. To make this value more meaningful at the program level, this predicted value should be multiplied by 1000 to give a predicted hospitalization/1000 rate. This can then be compared to the actual hospitalization/1000 rate.

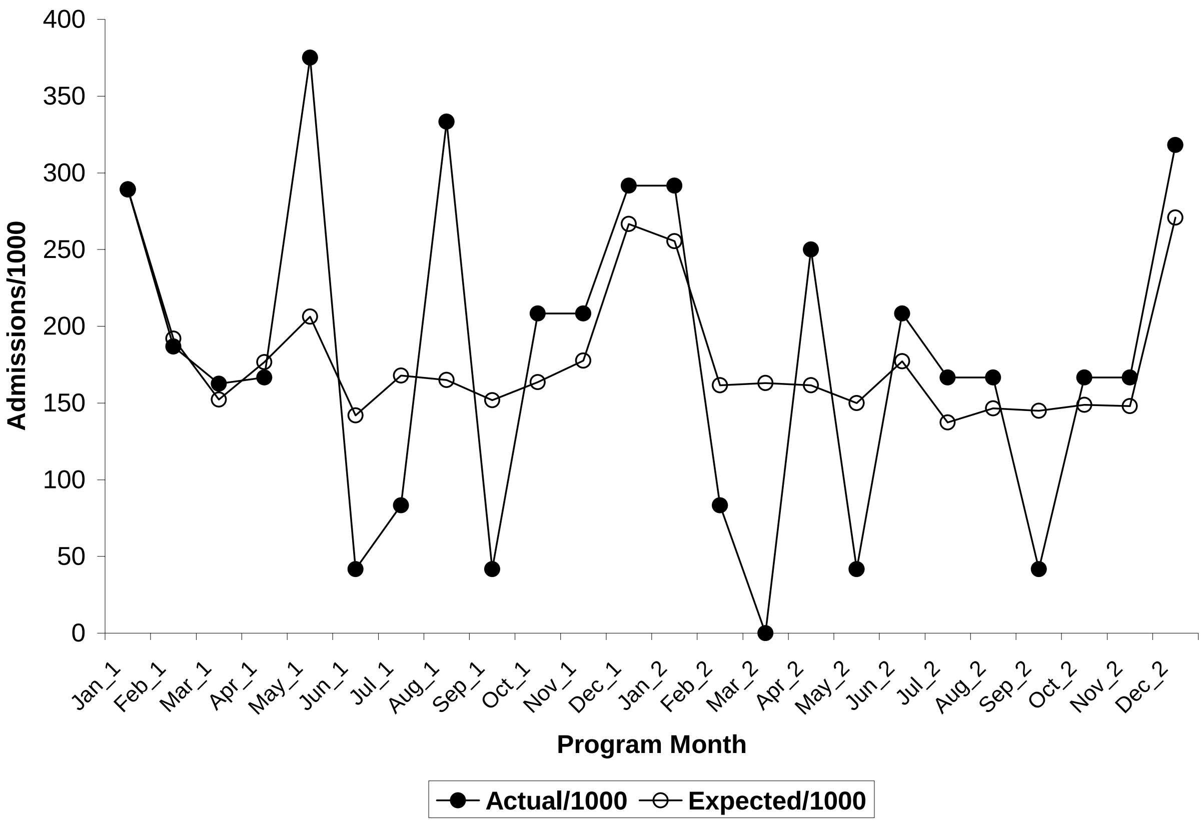
As shown, if all dummy variables values are set to 0 (those variables enclosed in parentheses in the equation), the resulting default value equals 0.289 hospital admits per member (or 289 admissions per 1,000 members), for the 1st month of tenure on the program, in January of the 1st program year. Likewise, the predicted value for 2nd month of tenure and February of the 1st program year equals .145 hospital admits per member (or 145 admits/1000 members).

USING THE REGRESSION MODEL RESULTS IN DISEASE MANAGEMENT

There are several ways to use the information gained from this regression model. First, it can used to predict the expected number of hospitalizations for any member given their month of tenure and month-of-the-year of interest. For example, Exhibit 4 displays the actual versus predicted hospitalization rate for new program enrollees (tenure = 1) at different months of the year. As shown, the model does a good job of predicting hospitalizations at this level, adjusting for the seasonal spikes appearing at December/January of each year. Similarly, Exhibit 5 presents a graphical display of the hospitalization rate in December of year 1 for all members at various points in their program enrollment (tenure). It appears that hospitalizations in December drop as a function of tenure, meaning that on average, as a person's tenure in the program increases, they are less likely to experience a hospitalization in December of year 1 (possibly mitigating the effect of seasonality in December). As shown, the model fits the data nicely at most points along the continuum. Similar analyses can be performed for any combination of tenure and month-of-year. This model allows a DM program to predict hospitalization rates for any month of the program, based on a participant's tenure. This type of information is important for planning DM program enrollment strategy as well as for setting realistic expectations on timing and the magnitude of expected program impact on the outcome variable.

This model may also be used to predict expected hospitalizations from one DM population to another. Assuming that the results are generalizable, this method could be used to establish expectations early on in the contracting phase between DM program administrators and purchaser (Linden, Adams & Roberts, 2004d). Once the program is implemented, monthly comparisons of actual admissions to predicted values will indicate how well the program is performing. The assumption of generalizability must be carefully examined, however, as there may be differences between the population from which the model was built and the new population which make generalizability difficult. For example, seasonality patterns exhibited from an older population in Florida may not hold true in a younger population in New York (*i.e.* in fact, there may prove to be an interaction between geography and age may be manifest in the data).

EXHIBIT 4
A COMPARISON OF ACTUAL *VS.* PREDICTED ADMISSION RATES
ALL MEMBERS WITH A TENURE OF 1 MONTH, THROUGHOUT THE 24 MONTH PROGRAM



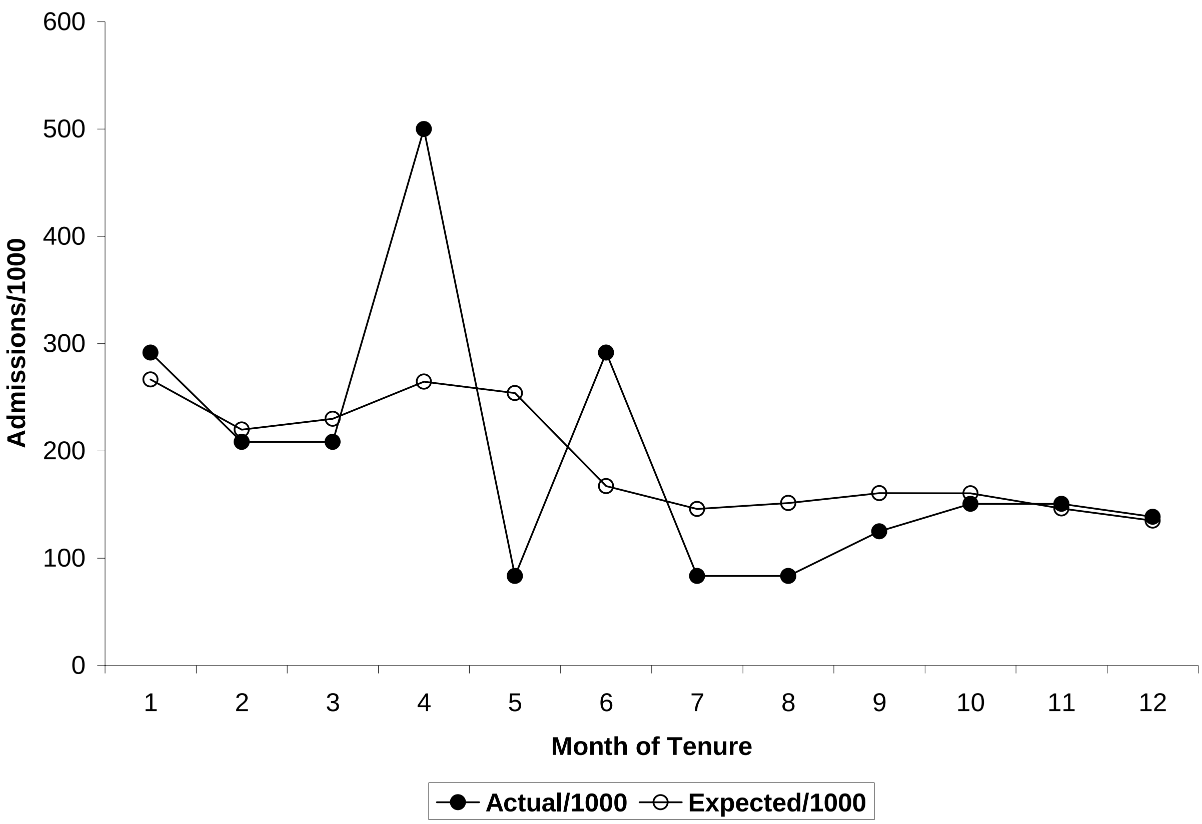
Values are derived from a simulated data set.

There are several ways in which program success can be established using this model. In most methods though, the difference between the predicted and the actual values is determined. A threshold can be set at a certain percentage above or below the expected value, and when the actual value falls outside of these parameters, some corrective action can be implemented. Refer to Linden, Adams & Roberts, 2003b for a comprehensive discussion on the various methods available for evaluating the program based on a model of this type.

MODIFICATIONS TO THE REGRESSION MODEL

In using the time-series regression, the model can be modified to incorporate other important covariates specific to DM. For example, interventions based on a psychosocial behavioral change model (Linden & Roberts, 2004) might introduce different levels and types of the intervention to the member at different stages throughout his or her tenure on the program This can be accounted for by adding into the model an additional set of dummy variables, consisting of 0's in all the months before the intervention is introduced, and 1's thereafter. An additional set of variables can be added for each supplementary intervention.

EXHIBIT 5
A COMPARISON OF ACTUAL VS. PREDICTED ADMISSION RATES
FOR THE MONTH OF DECEMBER IN PROGRAM YEAR 1



For members with tenures of 1 to 12 months (since the program was only 24 months long, tenure could not exceed 12 months past December of year 1). Values are derived from a simulated data set.

Length of time (tenure) as a health plan member may also be an important variable to consider. For some populations (*e.g.* young asthmatics) the access to primary care services and prescription drugs that come from health plan enrollment may be as critical to the outcome measure as enrollment in the DM program. Health Plan membership tenure could be introduced as either a continuous variable (months) or as a dummy variable (*e.g.* 0 for those in the plan less than 1-year and 1 for those with over 1 year of membership).

While hospital admissions were used as the outcome variable in this model, alternative important outcome measures could have easily been chosen. For example, instead of admissions, hospital days could have been selected. This would have given the advantage of knowing if the program had an impact, not only on reducing the likelihood of an admission, but also on reducing the length of stay (LOS) of that admission. This is an important consideration, since there currently is a disagreement over whether DM programs indeed impact LOS. Some believe that DM programs reduce the admission rate of diseased members, thereby leaving only the truly sick members to be hospitalized. Since these members are sicker, they may be hospitalized for longer stays. Others believe that DM programs do not influence LOS at all, and their impact is solely on reducing admissions.

Using hospital days as an outcome variable may also improve the association between utilization and costs. For example, if a medical/surgical day costs on average $2000, it would be easy to estimate projected costs based on this model. This is the preferred method rather than using cost as the outcome variable because of the multitude of factors influencing costs (Linden, Adams & Roberts, 2003a, 2003b).

Additionally, outcome variables may be chosen to represent quality of care measures, or level of compliance with evidence-based practice guidelines. For example, in a diabetic population, the outcome variable may be the number of members that achieve the 7 percent HbA_1C level. An independent variable set for tenure can be used to identify how long it takes a member in the program to achieve this desired level. Similarly, the relationship between acute asthma exacerbations, tenure and seasonality can be assessed. A seasonal spike during the spring season might be found, while fewer DM program participants with long program tenures experience an asthma attack.

Finally, there may be additional demographic characteristics that may be important explanatory variables, such as age, sex, social economic status, *etc.* that can be included in the model. However, as this is a time-series model, some of these factors will change over time. Therefore, the variable must be carefully chosen, determining which level of the variable is significant to the disease process or treatment.

CONCLUSIONS

This paper provides an additional tool for assessing DM program effectiveness. Program tenure and seasonality are two factors that are typically not controlled statistically. The regression model presented takes these two aspects of survival analysis and time-series analysis and merges them into one formula. Additional factors can be added to capture important time-dependent covariates, such as changing intervention strategies. Similarly, different outcome variable may be used in addition or in lieu of the current variable – hospital admissions.

As opposed to research-based or academic applications of regression analysis, this paper explains how to use the form and function of the regression equation to develop a simple yet effective means of predicting outcomes for a DM program at each point along the continuum. Similarly, if financial outcomes are a consideration for the DM program, utilization measures may be used and their associated actual costs compared to predicted values. In short, time-series regression is another useful tool in an analyst's repertoire for assessing DM program effectiveness that may be used in addition to, or in lieu of standard protocols currently in use in the industry.

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