White Paper

INGENIX®

Advances in Underwriting, #1

The power of predictive modeling for small group new business underwriting

Executive Summary

Predictive models have become well established tools in the disease management world. Can the documented predictive power of these models be transferred to underwriting applications? A recent large-scale research project conducted by Ingenix studied the ability of a pharmacy claims-based predictive model in projecting claims experience for new business in the small group market.

Findings:

- Using historical pharmacy data and predictive modeling technology substantially improved predictive capabilities for small group new business underwriting over standard demographic techniques.
- Predictive modeling on a group level was highly effective in cases where information was not available on every member of the group.
- High and low utilization groups were strongly predicted by using pharmacy data and predictive models.
- The increased accuracy with predictive modeling was most apparent for smaller and medium sized groups, although there were also observed benefits for large groups.

New Business Underwriting, Small Group Today

Traditional new business underwriting, especially in the small group market, is limited by the amount of information that carriers can obtain. The current method of medical underwriting driven by questionnaire responses is labor intensive and time consuming for both the insured and for carriers. Questionnaires produce information that is often incomplete or inaccurate, and may not even be asking the right questions to determine proper underwriting. Once the information is received, in-house underwriters may require extra information through follow-up calls and physician statements. The entire process is resisted by both brokers and clients.

Matching risk to premium involves another step, whether using debit manuals or projected dollar methods. Each method involves using resources that may not be kept current. In addition, the process is subjective in nature in that two underwriters may not reach the same conclusion when looking at the same information.

But what if a third party data source could be incorporated into the process? And what if this data was used to drive a predictive model that would provide a consistent basis for making underwriting decisions? In this study we show that just such a new process can provide an effective alternative to current practices.

Details of the Study

Intent

The purpose of this study was to establish the efficacy of predictive modeling for new business underwriting under conditions of less than perfect knowledge (i.e., the real world).

The Study Addressed the Following Questions:

- Pharmacy data provides a potential source of information on the relative risk of new individuals and groups, including their mix of therapeutic agents prescribed and, by inference, their likely medical condition. Can a predictive model using these data provide increased accuracy over traditional methods in projecting future risk for new enrollees?
- In some cases, pharmacy information will not be available for all new entrants into groups. What is the impact of less than complete data on predictive accuracy?
- How does predictive accuracy vary by group size and group level of risk?

Size of the Study

A large database was assembled for the study. In order to test different hypotheses, 30 months of claims and enrollment information was obtained. In order to avoid any systemic underwriting bias the information was drawn from

Group Size	% of Members	% of Groups	Cost PMPM
1 – 4	9.8%	73.8%	$ 309
5 – 9	5.6	11.7	224
10 – 19	6.0	6.3	216
20 – 49	9.0	4.2	214
50 – 99	9.1	1.9	216
100 – 249	11.8	1.2	215
250 +	48.7	0.8	219
Total	2.56 Million	85,166	$ 227/pmpm

Chart #1

three different health plans across different geographic census regions. Information was from a primarily non-elderly, commercial population and a variety of products. The study was comprised of 2,557,137 members and 85,166 real groups.

Group Breakdown

Group size based on number of subscribers (Chart #1).

Why Pharmacy Data

Getting adequate data to underwrite new business proposals is always difficult, especially for small groups. The standard industry practice has been to rely on self disclosure, both on an individual and group level basis with differing amounts of verification effort. Industry consolidation and the growth of PBMs have given rise to another source of information. With the subscriber's authorization insurers can now access databases which contain information on individual prescription histories known as pharmacy profiles. While not universal, the coverage in these databases is approaching 70% on a national basis.

Predictive Model Used

The predictive model used in the study is Symmetry's Pharmacy Risk Groups™ or PRGs™. The PRG model uses demographic and pharmacy claim information exclusively to develop risk scores. The PRG is capable of capturing and

PRG Approach

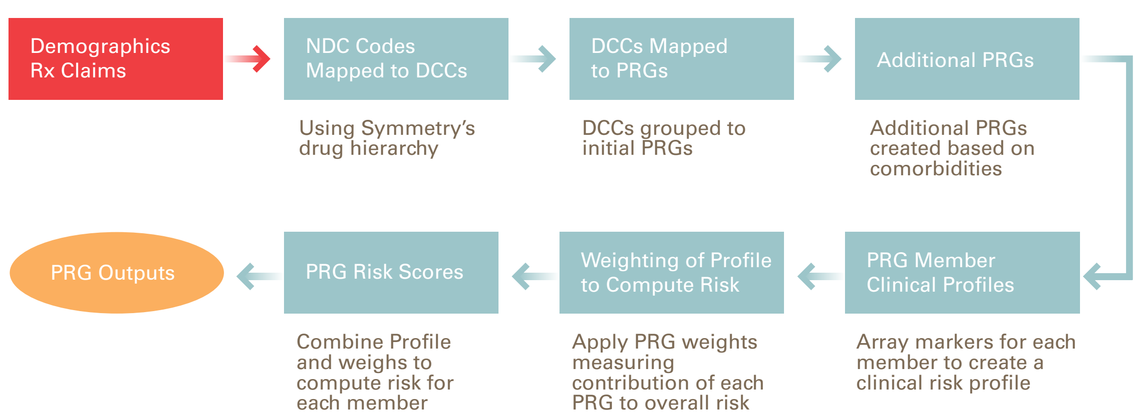


Chart #2

scoring multiple conditions and co-morbidities if present. These risk markers are rolled up into an individual risk score. The risk scores are then used to project medical expense (Chart #2).

Simulating Real World Conditions

The PRG model was tested under conditions that exist in the real world in order to validate its accuracy for day to day underwriting.

- **12-6-12** – Many tests of predictive models use a 12-month experience period to predict a subsequent 12-month period. While it would be ideal to be able to have all the available data on December 31 in order to quote January 1, this is not how the business works in reality. One feature of PRGs is the ability to set the model to project 12 months of claims expense based on a 12-month experience period with an intervening 6-month gap. While shortening the gap typically increases the accuracy of the predictive score, keeping the gap large provided a more realistic and stringent test of the model.

- **New entrants into groups** – The make up of any particular group is always subject to change. Complicating the underwriting process is how to evaluate the risk of a new entrant into a group where there is a shortened experience period for that individual. The PRG model is able to identify and to adjust its risk score for these shortened experience periods.

	Members	Demographic Risk	PRG Risk	Group PRG/ Demo Risk
Hits	7	0.8	1.1	
No Hits	3	0.9	0.9	
Total	10	0.83	1.04	1.25

Chart #3

For the time period of the study the groups were not scrubbed to maintain only individuals with full period experience. Natural changes, both new entrants and exits, were maintained.

- **Less than perfect data** – Underwriting involves making decisions with less than perfect knowledge. Pharmacy data may not be available for all new entrants for a group. While pharmacy data was available for all individuals in the study population (i.e., if an individual received a prescription, a record of the agent prescribed was included in the database), in order to simulate less than complete information the PRG model was tested under various scenarios where only a portion of the group member's pharmacy data was used. For the remainder of the group only an age/sex demographic risk factor was used. This is called the *hit rate*. In the following example a group has a 70 percent hit rate, meaning that 70 percent of the members had a PRG risk factor calculated from their pharmacy claims, with the remainder being assigned only their demographic risk factor. (Chart #3).

  Unlike previous studies which manufactured groups from individual members, all hit rates are from within real groups.

- **Predictions** – Predictions of future experience were made for each individual and aggregated to obtain a prediction for the group. In addition to PRGs, predictions were made for each group based on relative prior costs and an age-sex demographic model for comparison purposes.

Results of the Study

Methodology and Measures Used

As with any study there are certain methodological decisions that have to be made to reflect typical business practice. For most organizations, stop-loss mechanisms are used to manage risk and experience over a certain threshold. For this study, a $50,000 annual threshold was used for each individual. To accomplish this, actual future costs were truncated at $50,000 for each individual.

Results of the study are reported using several standard measures of accuracy:

← **Group R^2** - the percentage variation in total cost explained by the model.

← **Mean Absolute Prediction Error (MAPE)** – the average of the absolute difference between predicted and actual value in all test cases.

← **Positive Predictive Value (PPV)** – the percentage of predicted events that actually occurred.

Predictive Accuracy, Group R^2

The following chart shows the Group R^2 sorted by group size across three predictive models (age/sex demographic, actual prior claims, and PRGs) under the 12-6-12 scenario when utilizing the full data set and complete pharmacy information (i.e.,100 percent hit rate). It is interesting to note that the R^2 is higher for the PRG model with the exception of groups exceeding 250 subscribers when the actual group prior cost model catches up. This would confirm most underwriters' intuition of the size of a group needed for credibility, while showing the ability of predictive modeling to add value when predicting medium and larger sized groups.

Predictive Accuracy, Group MAPE ($ PMPM)

Similar to the Group R^2 presentation, the Group Mean Absolute Prediction Error (MAPE) shows the PRG model having superior predictive power over the other models, especially in the smaller and medium group size segments.

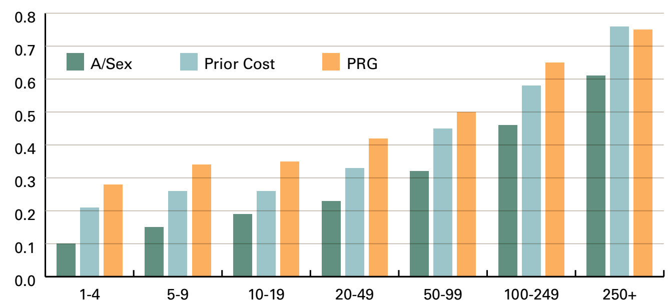
Incorporating Hit Rates

The previous two charts utilized all of the data from the study. The focus now turns to the predictive capability of the PRG model with less than complete information. The phenomenon of incomplete data was referred to above as the hit rate. The study simulated scenarios using various hit rates within groups.

Age and Sex Adjusted Risks and Costs

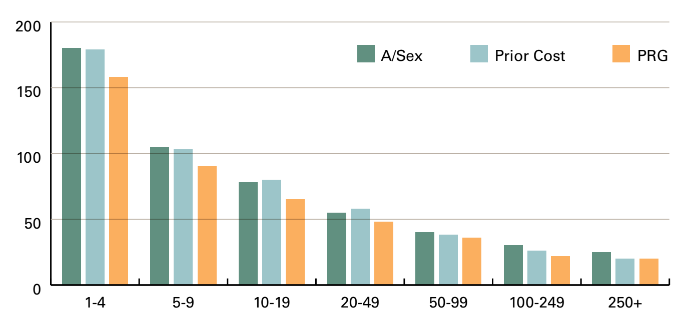
Underwriters often employ a rating formula that includes a factor for the age and sex of an individual and the age and sex composition of the group. As a result, PRG risk and future actual costs were adjusted by such a factor for the remainder of study analyses. In this way, the findings and measures reflect a level of risk over and above that

Predictive Accuracy
Group R^2



Group Size (Chart #4)
12-6-12 scenario using $50,000 threshold, Group R^2 describes the % variation in future across groups explained by a model. "Threshold" reflects future cost truncation for an individual prior to computing r-squared. Prior Cost model reflects truncation of individual prior costs at $50K before being used for prediction.

Predictive Accuracy - Group
Mean Absolute Prediction Error ($ PMPM)



Group Size (Chart #5)
12-6-12 scenario using $50,000 threshold, Mean absolute prediction arror (MAPE) represents the average absolute difference between predicted and actual experience across froups. "Threshold" reflects future cost truncation for an individual prior to computing r-squared. Prior Cost model reflects truncatio of individual prior costs at $50K before being used for prediction.

described by age and sex. Any measures of accuracy reflect added value over results based purely on a group's demographic composition. The new measure of PRG risk was called PRG/Demo.

Rating Tiers and Risk Cohorts

The study undertook a simulation of how groups could be assigned to different tiers for the purposes of rating. To do this, five tiers of equal size were created and 20 percent of the groups were assigned to each within a health plan. Groups in the highest rating tier were assigned based on having the highest PRG/Demo risk factor, the second tier was comprised of the next 20 percent of the groups based on PRG/Demo risk, and so on. Testing was based on the correspondence of each group's actual tier or risk cohort placement with their placement based on actual claim experience in the future 12-month period.

The following example shows the results of a simulation run on the data for all group sizes, assuming a 75 percent hit rate, and shows the correspondence between predicted risk cohort and actual risk cohort. (Chart #6)

These results show 41 percent of the groups predicted to be in the highest risk cohort were found to have future costs that placed them in the highest cost cohort, while only 9 percent were in the lowest cost cohort. A high level of correspondence was also shown for those groups placed in the lowest risk cohort. These results of 41 percent correspondence for both the highest and lowest risk cohorts indicate a result twice the level of correspondence that would be observed based on chance (20 percent).

	Actual Cost Cohort Top 20%	Actual Cost Cohorts Middle 60%	Actual Cost Cohort Lowest 20%	
Predicted Risk Cohort Top 20%	41%	50%	9%	100%
Predicted Risk Cohorts Middle 60%	18%	66%	16%	100%
Predicted Risk Cohort Lowest 20%	5%	54%	41%	100%

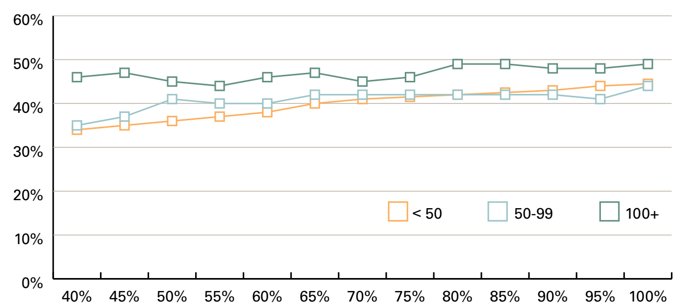
Chart #6

Simulation Results and Positive Predictive Value

Simulations were run comparing predictive power by differing combinations of hit rates and group sizes. Simulation results are reported in terms of positive predictive value. (Due to space constraints only a portion of our results are shown within this paper; anyone with a specific question is invited to query the authors.)

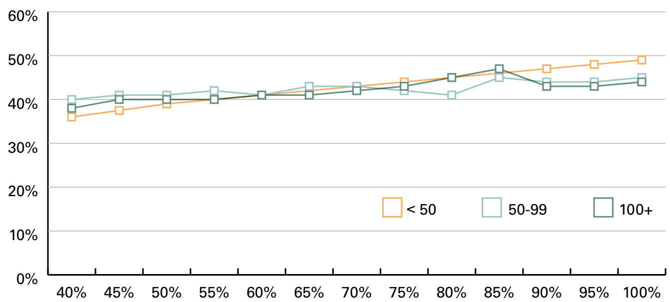
The following chart illustrates the simulation results by differing hit rates and group sizes when predicting the highest risk quintile. This is the probability that a group predicted to be in the highest 20 percent actually was in the highest 20 percent. Excellent results were observed for all group sizes and hit rate assumptions; as would be expected as group size and hit rate increase, the positive predictive value increases.

Simulation Results by Hit Rate
Highest Risk 20 Percent - Positive Predictive Value (PPV)
by Group Size



Hit Rate (Chart #7)
PPV is the percentage of groups predicted to be in to be in the top 20% of actual age-sex adjusted costs

Simulation Results by Hit Rate
Lowest Risk 20 Percent - Positive Predictive Value (PPV)
by Group Size

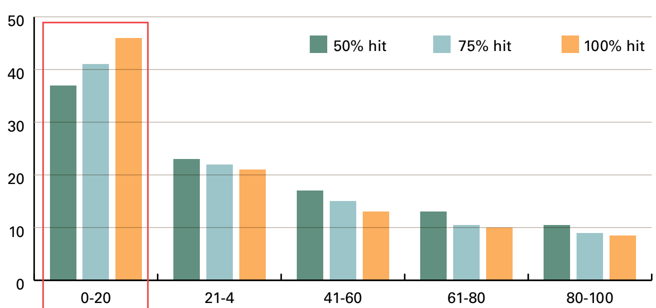


Hit Rate (Chart #8)
PPV is the percentage of groups predicted to be in to be in the bottom 20% that actually were in the bottom 20% of actual age-sex adjusted costs.

The chart above explores the same simulation in predicting the lowest risk quintile. Again this shows the probability that a group predicted to be in the lowest 20% actually was in the lowest 20%.

The last chart focuses in on the predictive ability of the model for groups of less than 5 subscribers. It illustrates the positive predictive value by quintile and hit rate when

Simulation Results - Groups less than 5
Lowest Risk 20% - Percentage by Actual Experience Percentile
"May have missed, but by how much?"



Hit Rate (Chart #9)
PPV is the percentage of groups predicted to be in to be in the top 20% of actual age-sex adjusted costs

comparing the predicted lowest quintile versus the actual experience quintile of the group. As shown, predictive modeling and pharmacy data provide significant added value even for the smallest groups in the study.

Uses of Predictive Modeling in the New Business Process

The results of this study demonstrate that there is compelling evidence for incorporating pharmacy profile information and predictive risk modeling into the new business underwriting process, especially in the small group market. The ability to gather pharmacy information and run predictive analytics is nearly instantaneous compared to the capabilities of traditional practices, and the anticipation is that underwriting results will be as good, if not better, than those derived from current practices.

INGENIX®

For Information: 800.765.6696 | insight@ingenix.com
Ingenix, Inc. | 12125 Technology Dr. | Eden Prairie, MN 55344
www.ingenix.com

About the Company

More than 1,200 payers now look to Ingenix for solutions to their complex business challenges. By integrating a diverse suite of products and services, Ingenix helps its clients increase revenue, manage medical costs, and simplify complex administrative and financial processes with powerful data, software, consulting, and outsourcing solutions. Consistent capital investment, stability of resources, and continual innovation have made Ingenix one of the largest and fastest-growing U.S. health care information companies.

About the Products Used in This Study

The Ingenix MedPoint pharmacy profiling capability and Symmetry PRG modeling technology used in this study are both part of the Ingenix Real-time Medical Underwriting solution that is available exclusively from Ingenix.

About the Authors

D. Bradford Johnson is director of Underwriting Services Development for Reden & Anders, Ltd., an Ingenix company, where he is responsible for the operational implementation of predictive modeling solutions in underwriting. Johnson earned an MBA in Finance from the University of Chicago and a Bachelor's degree in International Relations from the University of Southern California.

James Minnich has served as the national practice leader for Underwriting Services at Reden & Anders, Ltd. since 2000 and has more than 20 years of underwriting experience. He has helped many insurers and HMOs incorporate predictive modeling, electronic medical underwriting, and pharmacy claims data into their underwriting process. Minnich earned a Bachelor's degree from the University of St. Thomas and his CLU and ChFC designations from the American College.

Daniel Dunn is senior vice president of Research & Development for IHCIS, an Ingenix company, where he oversees the design and development of the company's market-leading predictive modeling and information solutions. Prior to joining IHCIS, Dunn worked as an economist at the Harvard University of Public Health. He holds a Ph.D. in Economics from the University of New Hampshire and has published more than 30 articles on a range of topics in health services research.

About This Series

The Advances in Underwriting Series from Reden & Anders and Ingenix is an occasional series of white papers and case studies highlighting advanced techniques for integrating new technology into the health care underwriting process.