ACTUARIAL SOCIETY OF SOUTH AFRICA

QUANTIFYING RISK, ENABLING OPPORTUNITY

Predictive modelling of future healthcare outcomes

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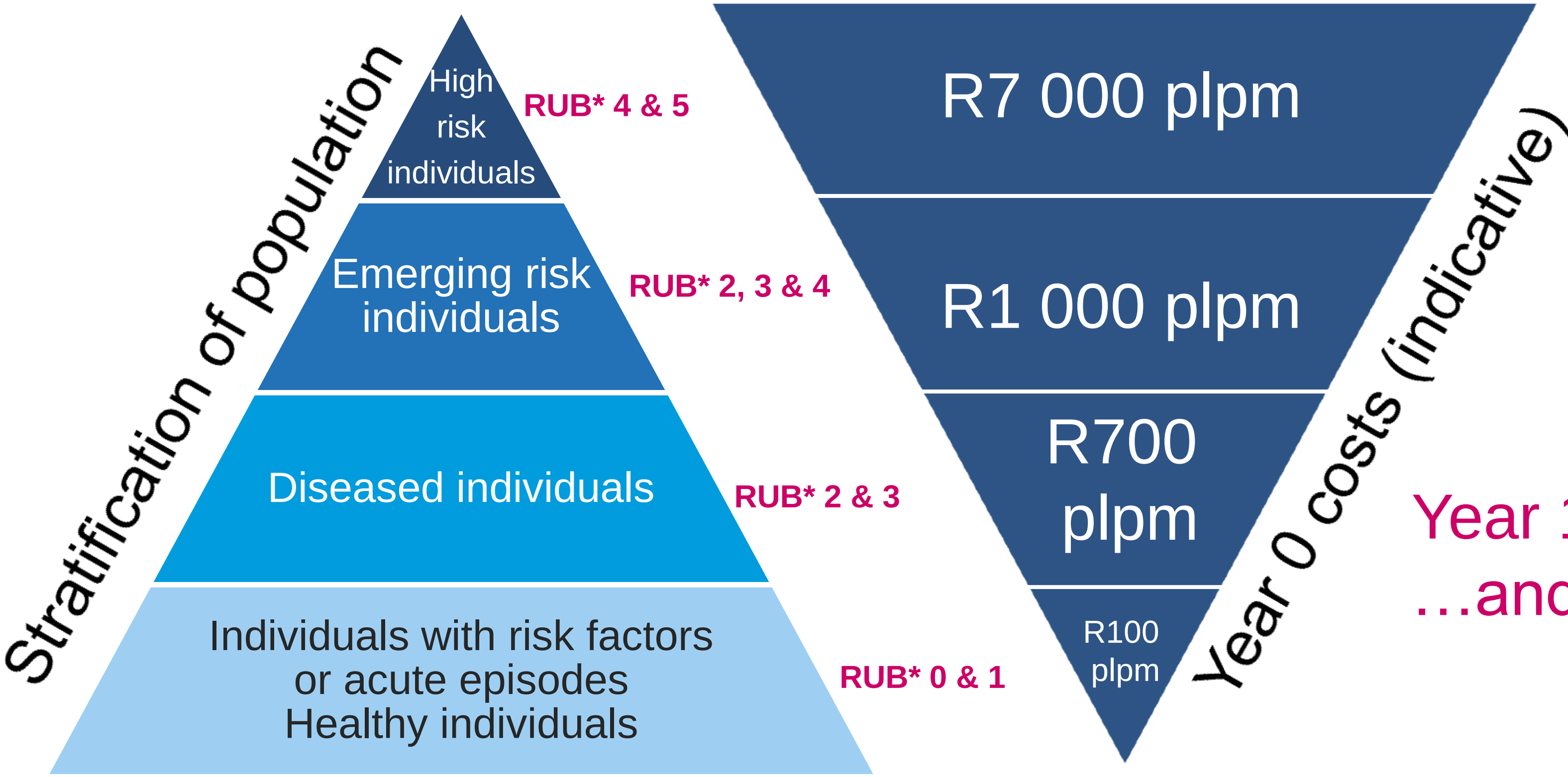
7 May 2015

Problem statement



Year 1 costs?
…and beyond?

*A Resource Utilisation Band or RUB is a collection of Johns Hopkins Adjusted Clinical Group® (ACG®) System Measures with similar concurrent relative resource use. ACGs are grouped into six RUB classes: 0 - No or Only Invalid Dx, 1 - Healthy Users, 2 – Low, 3 – Moderate, 4 – High, 5 - Very High

Agenda

1. Introduction and purpose
2. Possible uses
3. Data & methodology
4. Analysis of model coefficients
5. Model fit and predictive accuracy
6. Case study: diabetic lives
7. Practical considerations
8. Conclusion & references

Introduction and purpose

- This presentation builds on existing work and outlines a statistical model which predicts future utilisation and expenditure for South African medical schemes.

- The model enables predictions for subgroups of the population

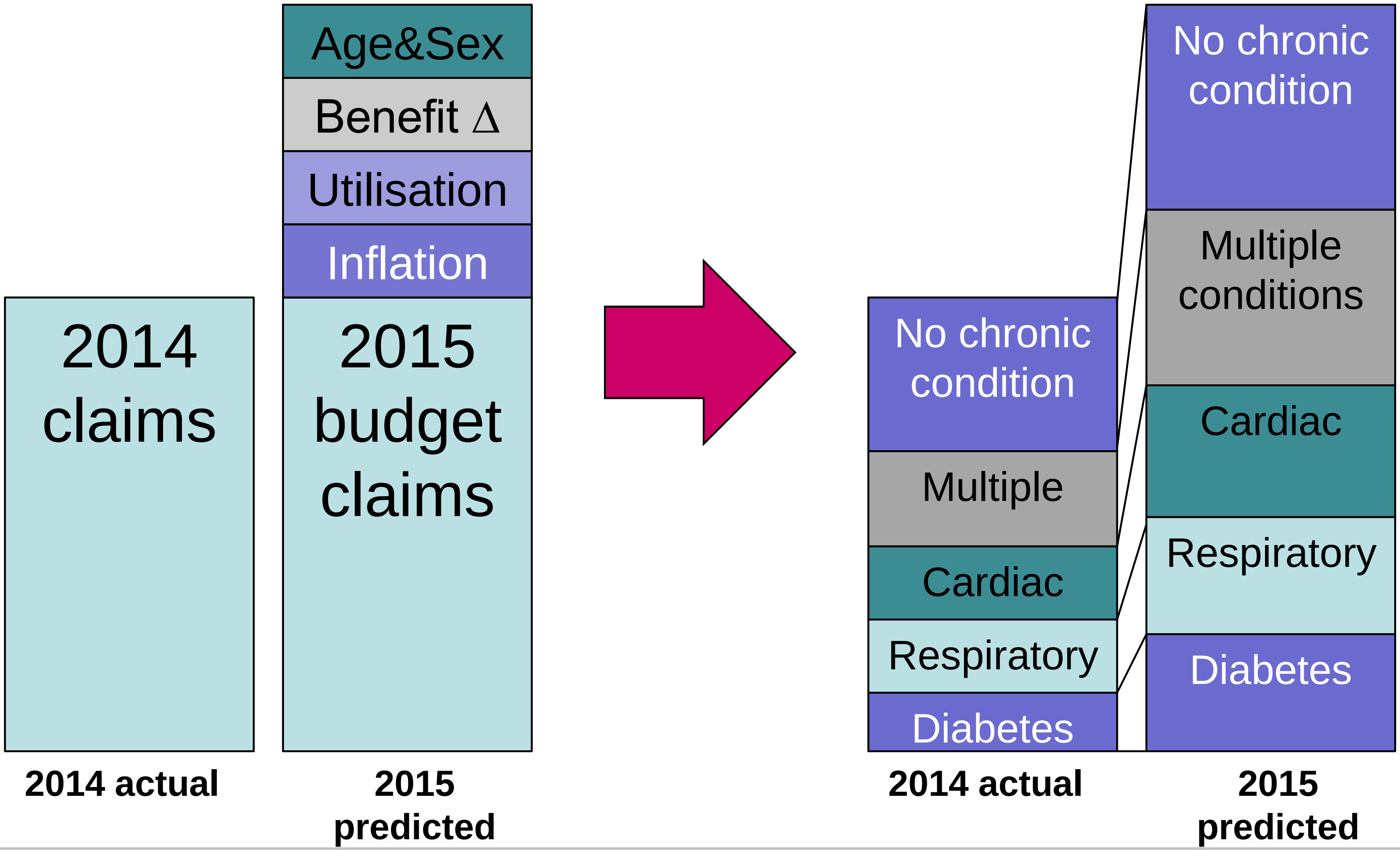
- The objective of the model is to accurately predict cost and utilisation for a grouping of lives of a reasonable size over different time periods.

Possible uses

The accurate prediction of future healthcare expenditure and utilisation has many applications in the South African medical schemes industry. These applications include, but are not limited to:

- Budgeting and pricing
- Monitoring / tracking against budget
- Making decisions on benefits and managed care interventions
- Measuring the value of managed care interventions
- Understanding disease progression
- Setting long term strategy
- Understanding cost and utilisation drivers

Budgeting and pricing



Value of managed care interventions

Overview of methods of measuring financial outcomes resulting from managed care interventions

- Randomised control trial } Prospective method
- Case matched cohorts
- Pre/post intervention assessment } Retrospective methods
- Savings approach
- Actual vs expected (all other things being equal)
- Using accurate prospective claims predictions as a benchmark

Source: The Value of Managed Care – Simon Dreyer's presentation at the ASSA CPD Day, 29 May 2014

Understanding disease progression and setting long term strategy

- Predict future costs for 1, 2, 3, 4, 5 years hence for a defined group such as diabetics with no or low co-morbidities
- Want to better understand and target interventions for target sub-populations
- Due to the nature of sub-populations cost and utilisation may be very different
- The model provides better insight into the subpopulation in terms of costs and utilisation
- Understand resource consumption

Understanding cost and utilisation drivers

- Model coefficients enable us to understand what increases risk, for example geographical region (proxy for access)
- Not only clinical factors, also demographic, choice of plan etc
- Investigate using additional independent variables to improve the predictive and prescriptive power of the model
- Incorporate impact of behaviour changes
- Model can be extended to cover outcomes more generally, for example quality

Data

- The data source was administrative data for Medscheme's client schemes.
  - Database consists of more than 3 million medical scheme beneficiaries

- Data was collected for the 2010 – 2014 benefit years from the membership database, the hospital utilisation management system and the claims processing system
  - Lacks clinical information
  - Other variables (e.g. socioeconomic status) have been shown to also have an impact on healthcare expenditure

Methodology

- Statistical regression modelling was used
- The philosophy employed was to keep the models as simple as possible in order to make the interpretation of results as easy as possible
- Multiple linear regression models were fitted first. More complex GLMs were only used where they provide a discernible improvement on predictions
- Data was split into hospital, ambulatory and chronic medicine cost
- No data trimming or truncation was applied
- Hospital admissions for trauma and neonates were removed

Dependent variables

Dependent variable	Chosen model
Hospital cost	Logistic regression for the probability of incurring hospital claims GLM with a Gamma distribution and log link function for hospital costs given that claims were incurred
Ambulatory cost	Multiple linear regression model
Chronic medicine cost	Multiple linear regression model

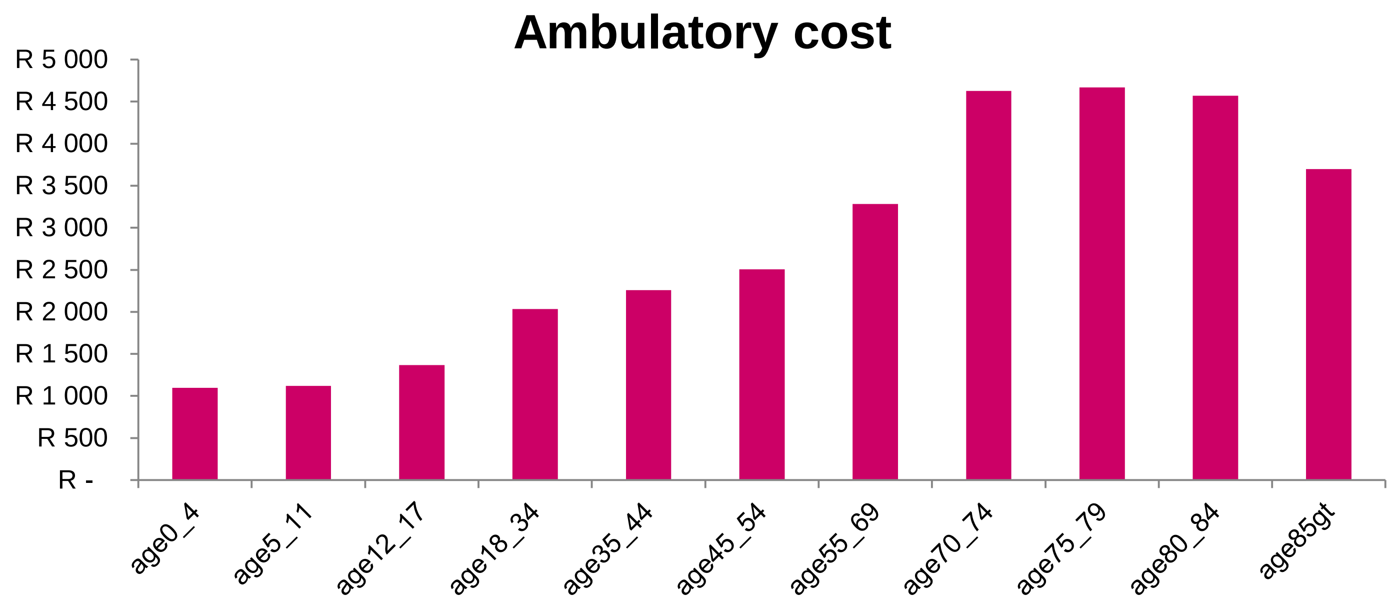
Total predicted cost is defined as the sum of the predicted hospital, ambulatory and chronic medicine costs

Independent variables

Variable name	Description
Age	The age of the beneficiary categorised into age bands
Gender	The gender of the beneficiary
Benefit richness	Benefit options were classified into high benefit, medium benefit, low benefit, hospital plan and low contribution plans
ACG risk markers	Risk markers from the Johns Hopkins ACG System ©
Chronic diseases	A set of indicator variables indicating whether a beneficiary suffers from a specified chronic illness
Previous cost	Categorised into a defined set of cost percentiles
Province	The province in which the beneficiary lives. Proxy indicator for access to healthcare.

Analysis of model coefficients

- 267 coefficients for each of the four models
- Shape over age looks sensible



Analysis of model coefficients

- Top 12 clinical variable coefficients

Variable	Variable description	Ambulatory cost	
gurx020	**Genito-Urinary / Chronic Renal Failure**	**R**	**169 201**
allx040	Allergy/Immunology / Immune Disorders	R	39 684
ind_chrdzs_ CRF	**Registered for Chronic Renal Failure Disease Management**	**R**	**39 356**
adm03	Transplant status	R	30 670
musx020	Musculoskeletal / Inflammatory Conditions	R	20 484
mal16	Acute leukemia	R	19 243
mal15	Malignant neoplasms, stomach	R	18 728
ren01	**Chronic renal failure**	**R**	**18 273**
mal13	Malignant neoplasms, pancreas	R	17 732
mal06	Malignant neoplasms, ovary	R	16 319
mal09	Malignant neoplasms, liver and biliary tract	R	15 841
mal10	Malignant neoplasms, lung	R	14 359

Analysis of model coefficients

Variable	Variable description	Probability of incurring hospital costs	Hospital cost given that hospital cost was incurred	Ambulatory cost	Chronic cost
Intercept	Intercept	-2.5498	10.4288	3 282.52	276.97
end06	Type 2 diabetes, **w/o complication**	0.0478	0.0029	277.59	18.98
end08	Type 1 diabetes, **w/o complication**	0.0461	-0.0193	759.71	794.48
endx030	Endocrine / Diabetes With Insulin	0.2271	0.1283	512.24	5 053.69
endx040	Endocrine / Diabetes Without Insulin	0.1056	0.0177	-115.44	183.15
ind_chrdzs_DM1	Registered for Type 1 diabetes	0.0151	0.0437	1 001.27	2 736.03
ind_chrdzs_DM2	Registered for Type 2 diabetes	-0.1284	-0.0029	-206.96	994.38

Condition	Probability of incurring hospital costs	Hospital cost given that hospital cost was incurred	Ambulatory cost	Chronic cost
Type 1 diabetic, insulin dependent	9.4%	R39 399	R5 556	R8 861
Type 2 diabetic, non-insulin dependent	7.4%	R34 424	R3 238	R1 473
Ratio of predicted probabilities / costs	**1.27**	**1.14**	**1.72**	**6.01**

Model fit

1. R-squared

$$R^2 = \frac{1}{n}\sum_{i=1}^{n}\frac{(y_i - \hat{y}_i)^2}{(y_i - \bar{y}_i)^2}$$

- Strictly only defined if estimates are based on least squares
- Because it squares each prediction error, it tends to be overly sensitive to the prediction error for individuals with large claims (Winkelman & Mehmud, 2007)
- It can be greatly affected by a relatively small number of cases with very large prediction errors (Dunne et al., 2006)
- Ideally large claims should be truncated when individual R-squared is used as a measure of predictive accuracy (Cumming et al., 2002)

Model fit

2. Mean Absolute Percentage Error (MAPE)

   – Standard definition (most commonly used to evaluate time series forecasts)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i}$$

   – Not defined where actual costs are zero

   – Penalises over-predictions severely

     - Upper bound of 100% to under-predictions, no upper bound to over-predictions

Model fit

MAPE (continued)

- Alternative definition (Winkelman & Mehmud, 2007)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{\bar{y}}$$

- Defined for zero actuals
- Over-predictions not penalised as severely
- It does not square the prediction errors (like R^2 does) and so is not overly sensitive to large claims (Winkelman & Mehmud, 2007)

Model fit

Model	R^2	R^2 (truncated data)*	MAPE**
1 Year prediction* **	22%	33%	82%
2 Year prediction* **	18%	27%	84%
3 Year prediction* **	15%	23%	86%
3 Year aggregated model******	29%	34%	72%

Notes:
A higher R^2 and a lower MAPE indicates better fit
* Data truncated at the 99th percentile
** Winkelman & Mehmud (2007) definition
*** Tested on an unknown validation set taken from a different year to that used to construct the model
**** Tested on an unknown validation set taken from the same years to those used to construct the model

Predictive accuracy

- Test the model against its objective, i.e. to accurately predict costs for groups of lives
- Predictions are tested for a future year, i.e. on a new dataset in a different benefit year to the year in which the model was fitted
- Individual predictions must be sufficiently accurate to allow for very accurate predictions on a group level
- The percentage prediction error is used as the accuracy measure

$$Percentage\ prediction\ error = \left| \frac{Actual\ cost\ for\ group}{Expected\ cost\ for\ group} - 1 \right|$$

Predictive accuracy

Grouping 1 – By ACG Resource Utilisation Band (RUB)

RUB in Year 0	% Lives	Predicted plpm (inflation adj)	Actual plpm	Absolute error	% prediction error
0 - Non-claimers	8%	226.65	189.16	37.49	16.5%
1 - Healthy claimers	16%	257.17	264.98	7.81	3.0%
2 - Low claimers	23%	394.02	389.77	4.24	1.1%
3 - Moderate claimers	42%	946.02	937.20	8.82	0.9%
4 - High claimers	9%	1 812.82	1 793.54	19.28	1.1%
5 - Very high claimers	2%	4 589.18	4 541.76	47.42	1.0%
Total	**100%**	**809.20**	**800.05**	**9.15**	**1.1%**

Predictive accuracy

Grouping 2 – By predicted cost bands

Predicted cost band	% Lives	Predicted plpm (inflation adj)	Actual plpm	Absolute error	% prediction error
Below 25th percentile	25%	138.55	159.83	21.28	15%
Between 25th and 50th percentile	25%	348.66	330.76	17.90	5%
Between 50th and 75th percentile	25%	670.94	660.59	10.34	2%
Between 75th and 90th percentile	15%	1 288.54	1 288.98	0.43	0%
Between 90th and 95th percentile	5%	2 026.82	2 015.70	11.11	1%
Above the 95th percentile	5%	4 580.98	4 362.51	218.48	5%

Predictive accuracy

Grouping 3 – By clinical group

Clinical group	# lives	Predicted plpm (inflation adj)	Actual plpm	% prediction error
Cardiovascular	493 568	2 408.33	2 490.48	3%
Respiratory	1 044 857	1 220.80	1 172.39	4%
Musculoskeletal	729 259	1 636.34	1 626.52	1%
Ear, Nose, Throat	1 225 237	933.00	878.49	6%
Gastrointestinal/Hepatic	741 278	1 405.87	1 371.66	2%
Psychosocial	295 276	1 820.52	1 688.05	7%
Endocrine	150 796	2 416.43	2 404.70	0%

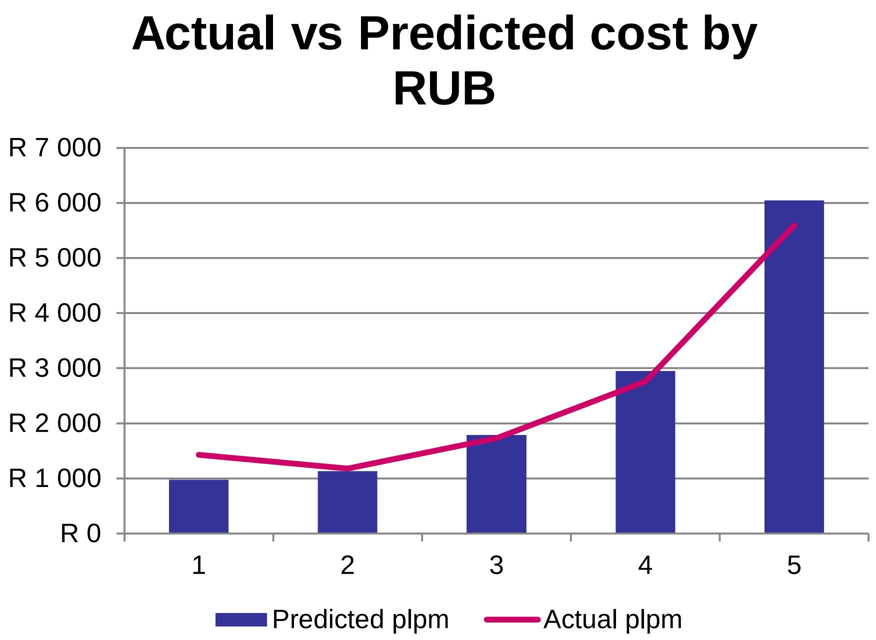
Case study: diabetic lives

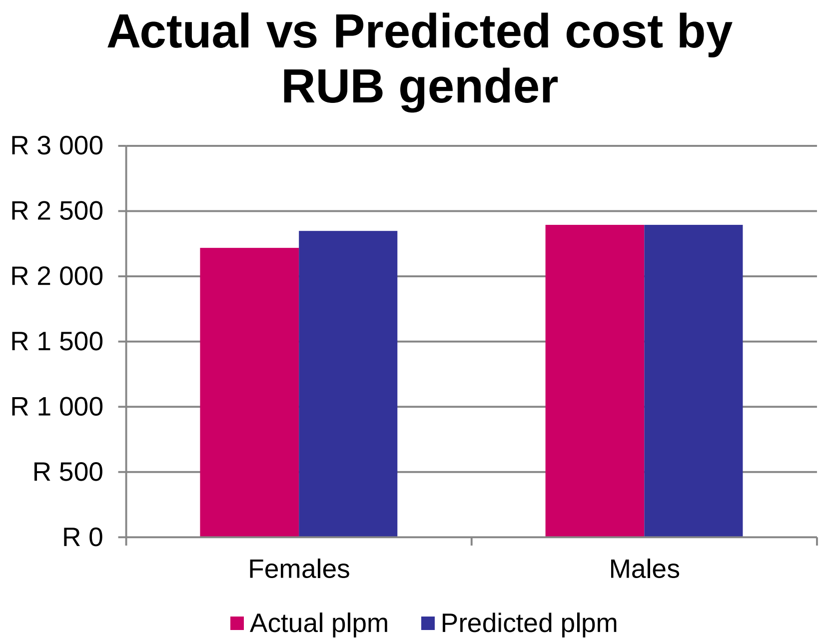
A sample of 90 373 beneficiaries with Type 2 Diabetes Mellitus was taken:

	Year 1	Year 2	Year 3
% prediction error	5%	2%	6%

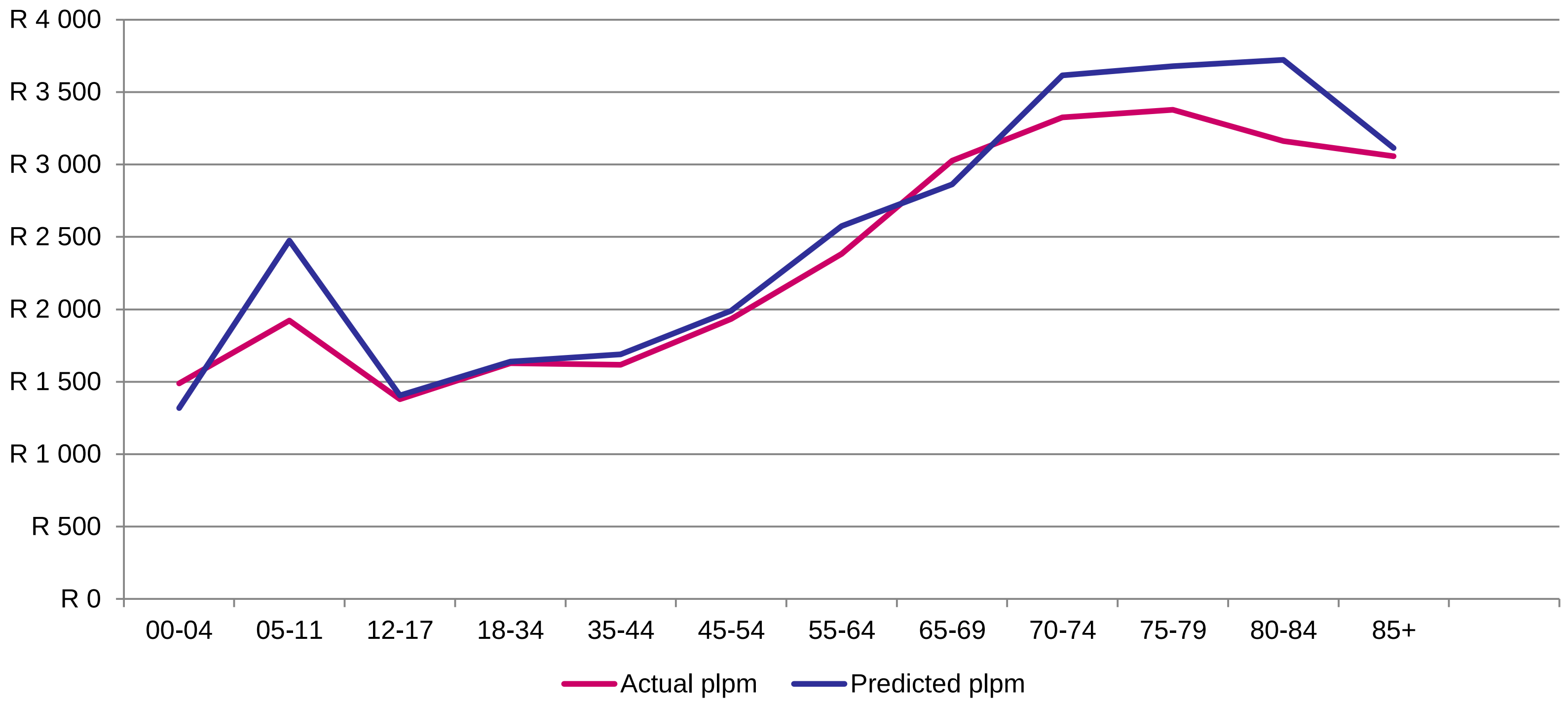
The model allows us to accurately predict costs not only for the subset of diabetics, but also for smaller subsets of the diabetic population

Case study: diabetic lives



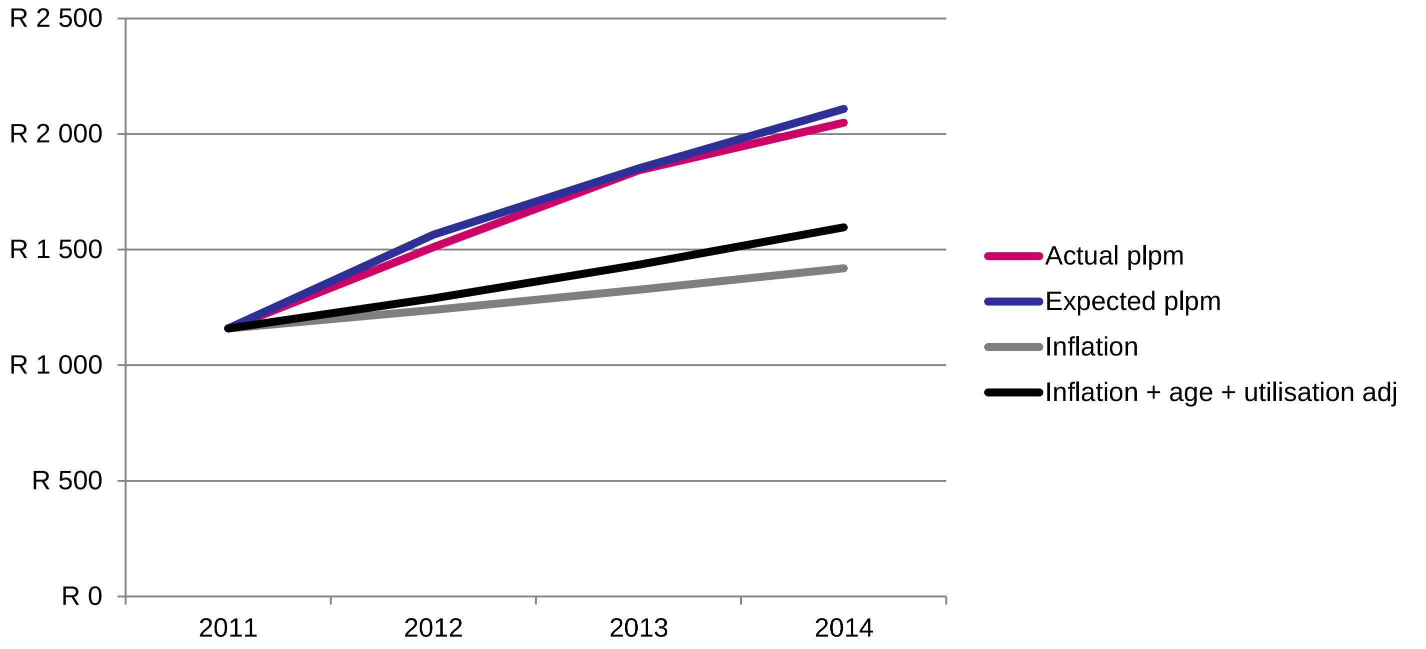


Case study: diabetic lives



Case study: diabetic lives

Predict cost forward for Type 2 diabetics with few co-morbidities



Practical considerations

An actual vs expected analysis makes sense (all other things being equal). However, there will be variation in:

- Inflation
- Benefit design
- New technology
- Option changes
- Demographics
- Member churn
- etc.

Adjustments need to be made for these factors if accurate prospective claims predictions are used for performance contracting

Conclusion

- We have demonstrated that, based on our predictive model, predictions for reasonably large groups of lives are very accurate
- This is a very useful result as it allows medical schemes to accurately predict future expenditure and utilisation for select groups of lives that may be of interest
- Accurate prospective claims predictions have a variety of potential uses

References

1. R Winkelman & S Mehmud A Comparative Analysis of Claims-Based Tools for Health Risk Assessment (2007)
2. D Shapiro, B Childs & C Getz Targeting High-Cost Beneficiaries in the Medium Term with Predictive Modelling Presentation at ASSA Convention 2013
3. R Cumming, D Knutson, B Cameron, B Derrick A Comparative Analysis of Claims-based Methods of Health Risk Assessment for Commercial Populations (2002)
4. Peter L. Flom & David L. Cassell Stopping stepwise: Why stepwise and similar selection methods are bad, and what you should use (2007)

Questions for the audience

- Are you comfortable with the predictive accuracy of the model?
- Are you comfortable with using accurate prospective claims predictions as a benchmark to measure managed care savings?

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