The Performance of Risk Adjustment Models in Colombian Competitive Health Insurance Market*

Alvaro J. Riascos Villegas[†]
Universidad de los Andes and Quantil

Eduardo Alfonso [‡]
Quantil

Mauricio Romero [§]
University of California San Diego

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[†]Faculty of Economics. E-mail: ariascos@uniandes.edu.co. Dirección: Facultad de Economía, Universidad de los Andes. Carrera 1 18A - 70 Bloque C, Bogotá DC.

[‡]Research and Development Department. E-mail: edalfon@gmail.com

[§]Department of Economics. E-mail: mauricioromerolondono@gmail.com

Abstract

We introduce new risk groups to a standard capitation formula and evaluate risk selection incentives of insurers. The study uses a unique data set of almost 24 million affiliates to Government's mandatory health insurance system. This data set is very rich in the sense of reporting all claims during year 2010, basic demographic variables, initial diagnostic, health services and pharmaceuticals used, etc. It compromises more than 300 million claims. Using this data set we construct several diagnostic related groups: an adaptation of the 3M algorithm, the Hierarchical Condition Categories (HCC) and an ad hoc diagnostic related group constructed by the authors. Using standard linear capitations formulas we evaluate incentives for cream skimming using several measures. In general, results show a notable improvement in the explanatory power of health expenditures by introducing the ad hoc diagnostic related groups to the standard Colombian risk adjustment formula. With the new risk groups the R^2 of the model is 13.53% as opposed to 1.45% of the current formula and the expected expenditure of the highest quintile of expenditures of the population is 71% of the actual expenditure as opposed to 27% of the current formula. This suggest there is much space for improving the current Colombian capitation formula using currently available information.

Keywords: Risk adjustment, Diagnostic Related Groups, Risk Selection.

JEL Codes: I11, I13, I18.

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1 Introduction

Since 1993 every Colombian is entitled to a comprehensive health benefit package. Individuals belong to one of two regimes according to their income. Those with higher income belong to the contributory regime, while individuals with lower income belong to the subsidized regime. The former is financed with a payroll tax, while the latter is financed through central government expenditure and part of the payroll taxes paid by individuals in the contributory regime. Originally, the health packages for the contributory and the subsidized regime where different. The packages were called *Plan Obligatorio de Salud*(POS) and *Plan Obligatorio de Salud Subsidiado*(POSS). The latter had less coverage. Nevertheless, the Constitutional Court ruled that both packages should be unified and this modification is expected to be implemented in 2013. The system is formally a competitive health insurance market were individuals in both systems get to choose a insurer, legally called *Entidades Promotoras de Salud* (EPS). This insurer is committed to provide all the services included in the POS or the POSS. In exchange, the insurer gets paid ex ante a yearly risk adjusted capitation payment.[1] Although affiliation is mandatory there are plenty of indirect ways to risk select individuals and, depending on the risk adjusted capitation formula, incentives for cream skimming may be large. The current capitation formula is a standard formula (linear regression) based on three risk factors: age groups, sex and three geographical regions. As it is well documented in the academic and applied literature, this risk factors have low predictive power and explain less than 2% of the variation in annualized health expenditures. To the extend that a large part of the unexplained variation on health expenditures is predictable, there is plenty of room for risk selection and for exploring ways to improve the risk capitation formula.

By now there is large academic literature that explores different risk factors and capitation formulas. For general surveys see Mihaylova et al. (2011), van de Ven & Ellis (2000), Ellis (2008) and Rice & Smith (2001). From the point of view of this paper the relevant literature focuses on the positive theory of risk adjustment as opposed to a normative theory that highlights the

[1] There is also an expost compensating mechanism that formally could be described as risk sharing of high costs where hight costs are defined based on specific diseases, currently renal chronic disease. In Colombia the current institutional arrangement allows for an expost redistribution of resources based on the prevalence of renal chronic disease per insurer. This paper focuses only on the prospective risk adjustment capitation payment.

importance of distinguishing normative and positive variables (see Schokkaert & de Voorde (2004) and Schokkaert & Van de Voorde (2000) for a discussion of the role of positive and normative variables in a conventional risk adjustment formula). By using a unique data set of over 24 million affiliates to Colombian mandatory health insurance plan in the contributory regime, we construct novel ad hoc diagnostic related groups based on readily available information, standard adapted diagnostic related groups studied in the academic literature and other variables that have been identified as good predictors of health expenditures (disability, hospitalization, etc.). Our approach is very pragmatic and it looks forward to evaluate the performance of several standard variables and more complex diagnostic related groups in terms of their predictive power of health expenditures and of the incentives for risk selection among special groups (i.e., the most expensive individuals). We go beyond the traditional linear models, well founded from a normative point of view, to models with interactions and with better predictive power. Our study is closely related to Beck (2000), Lamers (1998) among many others and specially Pope et al. (2004) where state of the art diagnostic related groups, Hierarchical Condition Categories (HCC) are evaluated in terms of their explanatory power of prospective health expenditures per person. In the same spirit as this literature on diagnostic related groups(DRG) we consider three different methods of grouping diagnostic codes. An adaptation of a 3M algorithm to Colombian data, an adaptation of the HCC algorithm as published in **?** and the authors own construction of diagnostic related groups based on medical experts assessment of related chronic conditions (renal chronic disease, HIV, arthritis, etc.).

This paper is organized as follows. The next section discusses the role of risk adjustment in competitive health insurance markets. Section 3 discusses the data available and the methods used (risk groups, models and performance measures). Section 4 presents the results and section 5 concludes.

2 Role of Risk Adjustment in Colombia

In this article we follow the definition of risk adjustment given by **?**: "the use of patient-level information to explain variation in health care spending, resource utilization, and health outcomes over a fixed interval of time, such as a year". Without regulation one would expect insurers to only insure lower cost individuals. This is, individuals that do not require medical attention often, and when they do, it is inexpensive. This would leave certain demographic groups, such as the elderly, without health care. The law prevents this types of actions in two ways. First, as mentioned above, insurers are legally obliged to provide insurance to any individual that requests it. Although in theory, its not legal for them to select who they insure, in practice there have been reports of slow affiliation process and missing applications.[2] To avoid this, current capitation payments in Colombia are adjusted by three risk factors: location, age and sex. This reduces the incentives of insurers to do cream skimming. Location is divided into three groups: Urban, rural and special regions. Age is divided into seven groups (see table below). Figure 1 shows the average per capita expenditure level per geographic group currently used (urban, rural and special)

	Age	Gender
Group 1	[0,1)	Both
Group 2	[1,4]	Both
Group 3	[5,14]	Both
Group 4	[15,18]	Male
Group 5	[15,18]	Female
Group 6	[19,44]	Male
Group 7	[19,44]	Female
Group 8	[45,49]	Both
Group 9	[50,54]	Both
Group 10	[55,59]	Both
Group 11	[60,64]	Both
Group 12	[65,69]	Both
Group 13	[70,74]	Both
Group 14	[75,∞)	Both

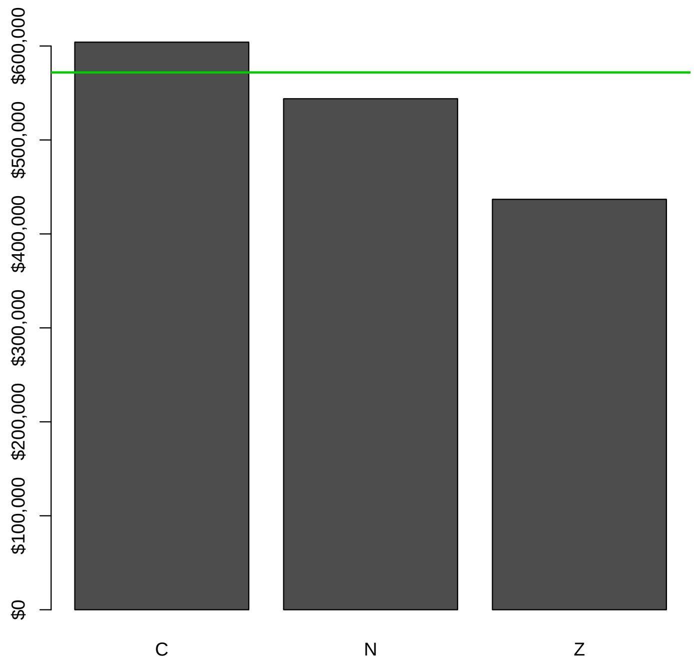
Table 1: Age and gender groups.

Figures 2, 3 and 4 show per capita expenditures by age, sex and the interaction of age and sex respectively.

The Ministry of Health and Social Protection, in charge of setting capitation payments, calculates the average expenditure per insured per day (the

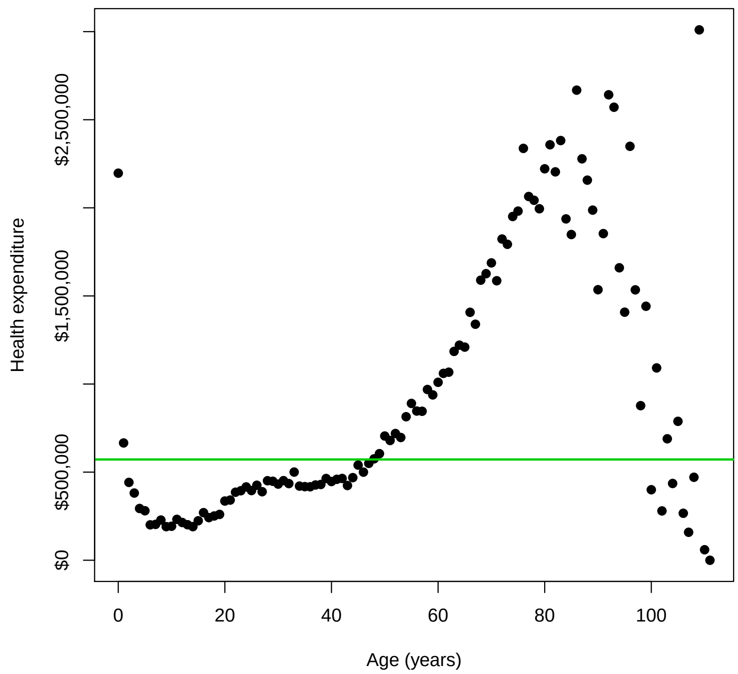
[2]Evidence in Colombia of risk selection and concentration of risks has been documented by Trujillo et al. (2010),Chicaíza (2005); Castano & Zambrano (2006) and Gómez-Suárez (2007).

Figure 1: Annualized health expenditure by region (weighted average by time of exposure)



sum of all reported expenditures of all affiliates divided by the number of days actually insured by all affiliates). The annualized value of this value is the capitation payment. By doing the same exercise on each cell (cell or risk group defined by the three factors), the Government determines the adjusted risk capitation payments for insurers. This model, which is equivalent to performing ordinary least squares estimation of a linear model with dependent variable annualized per capita expenditures and explanatory variable 42 dummy variables, each corresponding to a risk group, achieves an R^2 of 2%. This explanatory power is consistent with reported results in other countries (see van de Ven & Ellis (2000), Ellis (2008) and Rice & Smith (2001)). More importantly, this cell method with only three risk factor considerably over predict the low-expenditure affiliates (15 times for the lowest expenditure quintile), and under predict the high-expenditure affiliates (0.27) (see tables

Figure 2: Annualized health expenditure by age (weighted average by time of exposure)

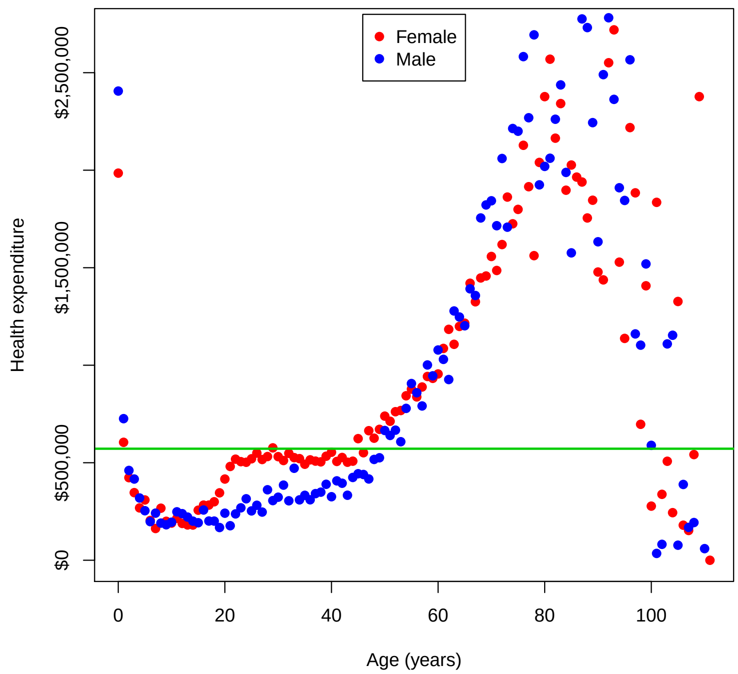


and discussion below). As a result, risk selection remains highly profitable.

There is obviously much space for improvement without compromising key normative properties of risk adjustment variables such as manipulability. For example figure 5 shows the average per capita expenditure per state. As can be seen, there is great variation in per state expenditure. Nevertheless, this figure must be evaluated with caution. If states with low average expenditure are mainly rural, remote areas, then it is possible that the low expenditure is due to low access to hospitals and doctors (an issue already present under the current adjustment formula). Reducing the amount that insures receive for each individuals in these areas could create an incentive not to offer services in those areas, and compromise other key normative properties: universality and equity.

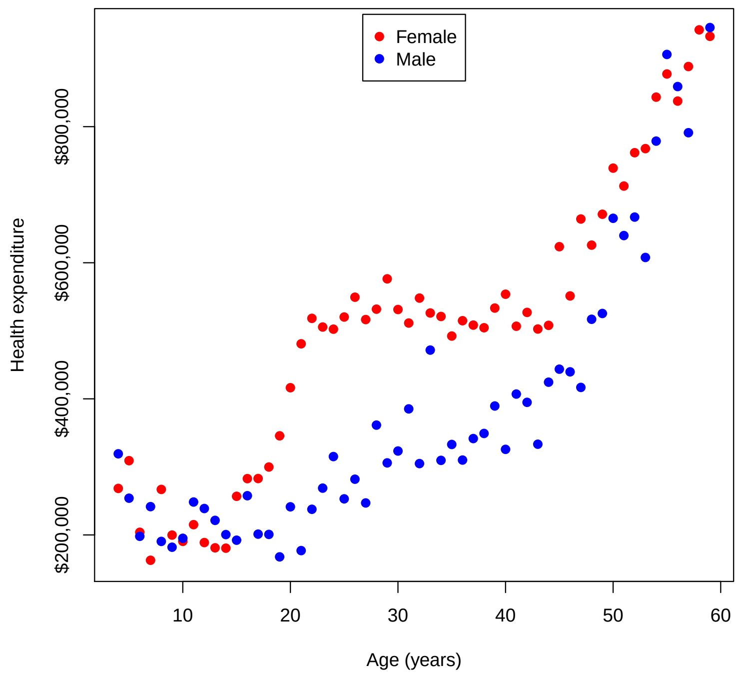
There is deep discussion regarding what should be the ideal risk adjust-

Figure 3: Annualized health expenditure by age and gender (weighted average by time of exposure)



ment formula in terms of variables and functional form. At the most basic level there is consensus in the fact that predictable risks for acceptable costs should be compensated although not necessarily fully compensated since insurers may incur in costs by risk selecting affiliates. Also, variables should be hard to manipulate, informations should be readily available and even if not all variable are to used to risk adjust, they should be used as explanatory variables in order to avoid problems of omitted variables in econometric estimations. Regarding the functional form, some authors provide strong arguments, based on social choice theory, for using linear models. The next section takes a pragmatic approach and by using new risk adjusters in Colombian system it provides and evaluates a set of methodologies that partially share some of the ideal properties mentioned before. In particular, the main guiding principle in the methods introduced in the next section is the search

Figure 4: Annualized health expenditure by age and gender (weighted average by time of exposure)



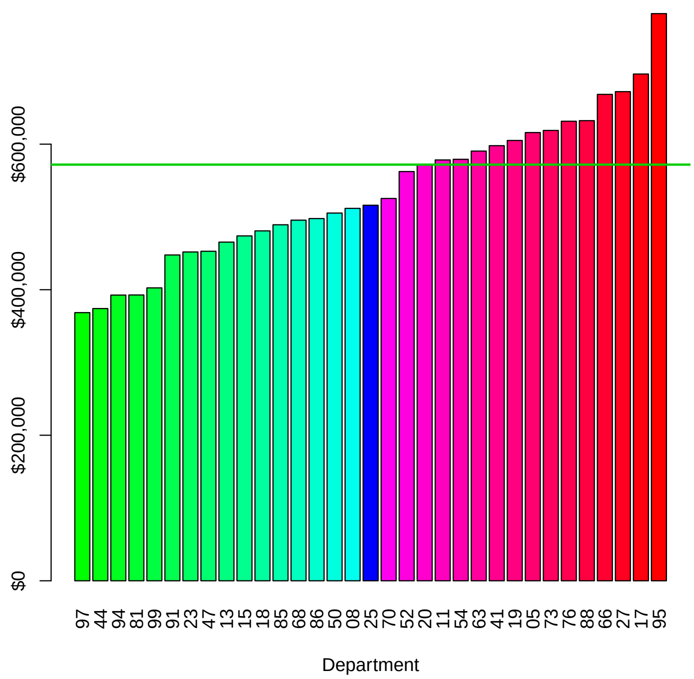
for models that make good predictions and the introduction of new variables that, although not completely immune to manipulation (i.e., up coding) may considerably reduce incentives for cream skimming.

3 Data and Methods

3.1 Data

The data used in this article corresponds to the information used by the Colombian Government to calculate the capitation payment and risk adjustment for the contributory regime (*Base de Suficiencia*). By law, all insurers must report all health services claimed by affiliates. This is a unique data set which contains more information than what is usual in many systems.

Figure 5: Annualized health expenditure by department (weighted average by time of exposure)



The data reports over 316 million claims of 24 million people during year 2010. It includes information regarding the individual, the service provided and initial diagnostic. More precisely, the variables found are:

- ID: Identification number of the patient.
- Sex.
- Date of birth of patient.
- State: The state where the service took place.
- Municipality: Municipality where the service took place.
- The date when the service was performed.

- Diagnosis: The CIE10 code for initial diagnostic.
- Activity: The activity performed by the physician classified according to a national coding system called CUPS.[3]
- Information on whether the service was ambulatory, domiciliary, urgent care or hospitalization.
- Length of stay: When the service required hospitalization, how long was it, in days.
- Value: The total value of the service provided.
- Copayment: The value of copayment.
- A categorical variable describing if the services included a pharmaceutical or if it was a visit to a physician.
- IPS Code: The code of the health provider of the service.

The information provided by health insurers goes through a clean up and validation process that we omit for simplicity.[4] Besides claims data we used a data set with basic affiliates information: identification number, the number of days that they were actually affiliated during the year.[5] We used to random samples of one million affiliates. One of the two databases is labelled the training data set and will be used to estimate all our models. The second database is labelled the test or validations data set, and is used to measure the performance of our models.

3.2 Methods

Two sort of risk factors were constructed. The first group consists of disability, previous hospitalization, specialist, morbidity and departments. The second group which is the key element behind all models is the construction of diagnostic related risk groups for Colombia based on the currently

[3]CUPS codes were mapped to CIE9CM codes using tables kindly provided by Fundación Valle del Lili, health service provider based in Cali. All errors are our own responsibility.

[4]See Bolivar & Axel Arcila (2012)

[5]Annual expenditures are annualized based on the proportion of the year in which the affiliate actually was insured.

available information. Three main types of diagnostic related groups were constructed. The first group is an adaptation of the CMS-HCC model to Colombia. The second is an adaptation of the 3M algorithm and the third one is an ad hoc method motivated by informally consulting with medical experts.

3.2.1 Risk groups

The details on how we adapted Medicare's CMS-HCC model and 3M algorithm can be found in the Appendix (to be completed). The ad-hoc diagnostic related groups we constructed consists of 29 groups of chronic diseases. For doing so we grouped CIE10 codes into one of the following broad diseases: Genetic and congenital abnormalities, arthritis, pyogenic arthritis and reactive arthritis, asthma, autoimmune disease, cancer insitu cervix, invasive cervical cancer, male genital cancer, breast cancer, cancer and skin melanoma, cancer digestive organs, respiratory system cancer, other cancer, other female genital cancer, lymphatic cancer and related tissue therapy, cancer, diabetes, cardiovascular disease - hypertension, cardiovascular disease, other long lasting lung disease, kidney - chronic renal failure, renal failure - kidney failure other, kidney - other renal, kidney long lasting, AIDS-HIV, seizure syndromes (epilepsy), transplants, tuberculosis. Further details are available form the authors upon request.

3.2.2 Models

As noted before, currently the Colombian Government uses a"cell-method" to perform the risk adjustment. The evaluation of this model and close variation of it are shown in tables $2, 3, 4$ and 5 as model 1. After those models come variations of the current model (number 1) that include disability, hospitalization, specialist or morbidity as an additional independent control (whenever the symbol $+$ is reported) or interacted with all variables (whenever symbol $\times$ is reported). Model 2 consists of the current model plus disability, hospitalization, specialist and morbidity. Model 3 interacts all variables of the current model with disability, hospitalization and specialist and adds morbidity without interacting it with any variable. The rest of the models are the same as model 3 plus different diagnostic related groups.

3.2.3 Performance measures

We used three standard all purpose validation techniques for the predictive performance of statistical models: R^2, Mean Absolute Predictive Error (MAPE) and Cummings Predictive Error. The first measure is reported as usual, the second one is reported relative to average expenditure of the population (capitation). Cummings predictive error is similar to R^2 except that it is the absolute deviation rather than the square of deviations what matters. These measures are reported both for in sample and out of sample predictions. We use the training sample to estimate the models and the testing sample to evaluate performance.

To evaluate the incentive for scream skimming after risk adjusting capitation using the different models we measure the ability of each model to explain the lowest and highest quantiles. In both cases the predicted expenditure of the group (the lowest or highest quintile) is measured relative the actual expenditure in the group. The exercise is also reported for in sample and out of sample.

Finally, to further explore incentives for risk selection, we measure the percentage of profitable affiliates after risk adjustment for each model, the maximum potential profit and the maximum potential profit as a percentage of expenditures.

4 Results

Tables 2 and 3 tell a similar story which means that model performance is somewhat independent of using as independent variable actual expenditure or annualized expenditures. Therefore we shall focus on only one of them, table 3, for convenience. The first clear message from results in table 3 is that the current model explains a small fraction of expenditures variations as measured by the R^2 statistic. This is consistent with many other studies that show that demographic factors are unable to explain more than 3 or 4 percent of health expenditures per capita. Disability and morbidity do not help much but hospitalization and specialist add substantial explanatory power the model. In particular, interacting all the current variables with a dummy of hospitalization the model increases its R^2 from 1.02% to 6.36%. This improvement is also true of the other two performance measures. Nevertheless the most outstanding result is related to the explanatory power of diagnostic related groups and, in particular, the ad hoc groups constructed for this paper that raises the R^2 of models 2 and 3 to levels close to 12%. Again this is consistent with results reported for similar models that use diagnostic related groups as independent variables to explain per capita health expenditures. Again the results do not change when we focus on the other two broad performance measures.

From the point of view of measures of incentive for risk selection it is more important to measure the predictive power of models with respect to special groups of affiliates. In particular, we measure the expected profit of insurers on those affiliates that turn out to be the least and most expensive. Table 4 reports the results for all models of predicted expenditures for the lowest quintile of expenditures (Q1) and the highest quintile (Q5) relative to actual expenditures of that group. The table shows that all models over predict expenditures of the least expensive and therefore this are likely to be profitable affiliates. On the other hand all models under predict expenditures of the most expensive group. This shows that in all models there remains incentives for risk selection but there are obvious advantages of risk adjusting using some of the more sophisticated models evaluated in this paper. In particular, the model with DRGs (the adaptation of 3M algorithm) has the best predictive power out of sample (expected predicted expenditures out of sample of the highest quintil are 84% of actual costs). Second in its ability to reduce incentives for risk selection, is the ad hoc model for which the predicted expenditures out of sample of the highest quintile is 74% of actual costs.

Finally, we address a third set of measures for evaluating incentives for reducing risk selection. The first column of table 5 (in the estimation and validation sample), measures the percentage of affiliates that are profitable under each model. The second and third column (in the estimation and validation sample) reports maximum potential profit within each group as a percentage of total revenues. Once again the model with ad hoc diagnostic related groups performs well relative to the other models.

5 Conclusion

In this paper we have used a unique data set of over 300 million health insurence claims for year 2010. Using this data set we constructed several diagnostic related groups: an adaptation of the 3M algorithm, the Hierarchical Condition Categories (HCC) and an ad hoc diagnostic related group constructed of the authors. We evaluated the performance of standard risk adjustment formulas using three different type of measures: all purpose statical performance measures such as R^2, $MAPE$ and Cummings measure and others tailored made to evaluate risk selection incentives. Over all we show that a simple ad hoc diagnostic related groups constructed by the authors improves considerably the performance measure of the current Colombian risk adjustment formula in terms of explanatory power and incentives of risk selection. With these risk groups the R^2 of the model is 13.53% as opposed to 1.45% of the current formula and the expected expenditure of the highest quintile of expenditures of the population is 71% of the actual expenditure as opposed to 27% of the current formula. This suggest here is much space for improving the current Colombian capitation formula using currently available information.

Table 2: Individual-level predictive performance indicators (actual expenditure)

Model	Estimation sample			Validation sample		
	R^2(%)	$MAPE$	CPM(%)	R^2(%)	$MAPE$	CPM(%)
Until 2009	1.47	1.31	6.12	1.20	1.31	5.41
(1): Current	1.65	1.30	6.68	1.33	1.31	6.00
AgeGroup*Gender*Zone	1.67	1.30	6.75	1.33	1.30	6.06
Age*Gender*Zone+Age2+Age3	1.18	1.34	3.99	1.00	1.34	3.28
AgeGroup*Gender*Zone*City	1.67	1.30	6.75	1.33	1.30	6.06
AgeDummies*Gender*Zone	1.76	1.30	6.77	1.30	1.31	6.03
(1) + Disability (D)	1.85	1.30	6.88	1.56	1.30	6.27
(1) x Disability (D)	1.91	1.30	6.89	1.56	1.30	6.23
(1) + Hospitalization (H)	5.90	1.21	13.24	5.00	1.21	12.76
(1) x Hospitalization (H)	7.92	1.13	18.90	6.52	1.13	18.45
(1) + Specialist (S)	3.72	1.22	12.50	3.10	1.23	11.74
(1) x Specialist (S)	4.18	1.17	16.25	3.44	1.17	15.44
(1) + Morbidity (M)	1.66	1.30	6.70	1.34	1.31	6.01
(1) + Chronic	11.03	1.16	16.55	9.20	1.17	15.67
(1) + DRG	12.75	1.08	22.65	6.29	1.17	15.81
(1) + HCC	4.91	1.24	11.26	4.27	1.24	10.63
(1) + D + H + S	6.91	1.24	10.68	5.90	1.25	10.03
(1) x D x H x S	9.76	1.05	24.92	7.71	1.05	24.30
(2): (1) + D + H + S + M	6.95	1.25	9.97	5.94	1.26	9.32
(3): (1) x D x H x S + M	9.79	1.05	24.41	7.73	1.06	23.77
(2) + Chronic	13.69	1.17	16.07	11.54	1.18	15.22
(2) + DRG	13.25	1.13	19.17	6.77	1.21	13.12
(2) + HCC	8.73	1.23	11.96	7.55	1.23	11.31
(3) + Chronic	15.58	1.04	25.20	12.65	1.05	24.37
(3) + DRG	15.08	1.00	28.12	8.15	1.10	20.53
(3) + HCC	11.25	1.04	25.07	9.10	1.05	24.48

R^2: R-squared calculated as the percentage of variation in individual expenditure explained by the model.$MAPE$: Mean absolute prediction error expressed as a proportion of total mean expenditure.CPM: Cumming's Prediction Measure. For a detailed discussion of these measures see **?**

Table 3: Individual-level predictive performance indicators (annualized expenditure)

Model	Estimation sample			Validation sample		
	$R^2(\%)$	$MAPE$	$CPM(\%)$	$R^2(\%)$	$MAPE$	$CPM(\%)$
Until 2009	1.27	1.31	4.29	1.02	1.31	3.52
(1): Current	1.45	1.30	4.86	1.15	1.31	4.13
AgeGroup*Gender*Zone	1.47	1.30	4.93	1.16	1.30	4.19
Age*Gender*Zone+Age2+Age3	0.98	1.34	2.12	0.82	1.34	1.35
AgeGroup*Gender*Zone*City	1.47	1.30	4.93	1.16	1.30	4.19
AgeDummies*Gender*Zone	1.56	1.30	4.95	1.12	1.31	4.15
(1) + Disability (D)	1.65	1.30	5.06	1.38	1.30	4.39
(1) x Disability (D)	1.71	1.30	5.07	1.38	1.30	4.36
(1) + Hospitalization (H)	5.71	1.21	11.54	4.83	1.21	11.02
(1) x Hospitalization (H)	7.73	1.13	17.32	6.36	1.13	16.82
(1) + Specialist (S)	3.53	1.22	10.79	2.92	1.23	9.98
(1) x Specialist (S)	3.98	1.17	14.62	3.27	1.17	13.75
(1) + Morbidity (M)	1.46	1.30	4.88	1.16	1.31	4.13
(1) + Chronic	10.85	1.16	14.92	9.04	1.17	13.99
(1) + DRG	12.57	1.08	21.14	6.12	1.17	14.12
(1) + HCC	4.71	1.24	9.53	4.10	1.24	8.85
(1) + D + H + S	6.72	1.24	8.94	5.73	1.25	8.23
(1) x D x H x S	9.58	1.05	23.46	7.54	1.05	22.78
(2): (1) + D + H + S + M	6.76	1.25	8.21	5.77	1.26	7.51
(3): (1) x D x H x S + M	9.61	1.05	22.93	7.57	1.06	22.25
(2) + Chronic	13.52	1.17	14.43	11.38	1.18	13.52
(2) + DRG	13.07	1.13	17.59	6.61	1.21	11.38
(2) + HCC	8.55	1.23	10.24	7.39	1.23	9.54
(3) + Chronic	15.41	1.04	23.74	12.49	1.05	22.86
(3) + DRG	14.90	1.00	26.72	7.98	1.10	18.94
(3) + HCC	11.07	1.04	23.61	8.94	1.05	22.97

R^2: R-squared calculated as the percentage of variation in individual expenditure explained by the model. $MAPE$: Mean absolute prediction error expressed as a proportion of total mean expenditure. CPM: Cumming's Prediction Measure. For a detailed discussion of these measures see **?**

Table 4: Predictive ratios for non-annualized expenditure quintiles

Model	Estimation sample		Validation sample	
	Q1	Q5	Q1	Q5
Until 2009	15.48	0.26	15.53	0.27
(1): Current	15.22	0.27	15.26	0.28
AgeGroup*Gender*Zone	15.20	0.27	15.24	0.28
Age*Gender*Zone+Age2+Age3	16.16	0.25	16.22	0.25
AgeGroup*Gender*Zone*City	15.20	0.27	15.24	0.28
AgeDummies*Gender*Zone	15.15	0.27	15.18	0.28
(1) + Disability (D)	15.15	0.28	15.19	0.28
(1) x Disability (D)	15.13	0.28	15.19	0.28
(1) + Hospitalization (H)	8.41	0.52	8.52	0.53
(1) x Hospitalization (H)	8.78	0.55	8.88	0.56
(1) + Specialist (S)	9.27	0.45	9.38	0.45
(1) x Specialist (S)	9.36	0.47	9.46	0.48
(1) + Morbidity (M)	15.21	0.27	15.24	0.28
(1) + Chronic	8.94	0.53	8.97	0.53
(1) + DRG	3.52	0.76	0.76	0.76
(1) + HCC	11.47	0.41	11.47	0.41
(1) + D + H + S	5.26	0.61	5.42	0.62
(1) x D x H x S	5.99	0.65	6.08	0.66
(2): (1) + D + H + S + M	5.08	0.61	5.24	0.62
(3): (1) x D x H x S + M	5.83	0.65	5.92	0.66
(2) + Chronic	3.63	0.71	3.76	0.72
(2) + DRG	1.99	0.78	1.92	0.84
(2) + HCC	4.07	0.66	4.19	0.67
(3) + Chronic	4.37	0.73	4.44	0.74
(3) + DRG	3.06	0.81	1.15	0.84
(3) + HCC	4.91	0.69	4.96	0.70

Q1: lowest expenditure quintile. Q5: highest expenditure quintile.

Table 5: Maximum Potential Profit of Risk Selection

Model	Estimation sample			Validation sample		
	Enrolled	Profit		Enrolled	Profit	
	(%)	($)	(%)	(%)	($)	(%)
Until 2009	81.17	264.32	79.10	81.27	264.49	79.02
(1): Current	81.14	262.74	78.78	81.22	262.73	78.71
AgeGroup*Gender*Zone	81.15	262.55	78.72	81.22	262.56	78.66
Age*Gender*Zone+Age2+Age3	78.69	270.31	79.85	78.74	270.32	79.82
AgeGroup*Gender*Zone*City	81.15	262.55	78.72	81.22	262.56	78.66
AgeDummies*Gender*Zone	80.84	262.50	78.74	80.93	262.72	78.70
(1) + Disability (D)	80.99	262.19	78.68	81.06	261.98	78.63
(1) x Disability (D)	80.95	262.16	78.71	81.02	262.16	78.65
(1) + Hospitalization (H)	65.68	244.28	73.60	65.62	243.63	73.62
(1) x Hospitalization (H)	75.77	228.33	71.97	75.78	227.69	71.96
(1) + Specialist (S)	66.92	246.37	73.19	67.00	247.30	73.27
(1) x Specialist (S)	77.48	235.79	71.90	77.53	237.36	72.10
(1) + Morbidity (M)	81.02	262.69	78.76	81.09	262.71	78.70
(1) + Chronic	76.09	234.95	73.33	76.15	235.14	73.46
(1) + DRG	39.18	217.79	65.38	27.19	214.59	68.73
(1) + HCC	78.76	249.86	75.94	78.86	249.86	75.86
(1) + D + H + S	39.40	251.48	70.07	39.44	251.50	70.10
(1) x D x H x S	73.76	211.38	67.15	73.85	212.09	67.19
(2): (1) + D + H + S + M	45.26	253.48	70.08	45.26	253.49	70.11
(3): (1) x D x H x S + M	69.59	212.83	67.16	69.72	213.56	67.18
(2) + Chronic	40.58	236.32	68.58	40.62	236.33	68.73
(2) + DRG	38.96	227.58	65.94	37.57	251.74	68.76
(2) + HCC	43.32	247.88	69.12	43.35	247.84	69.12
(3) + Chronic	62.07	210.60	67.14	62.21	210.93	67.24
(3) + DRG	46.16	202.37	63.45	34.56	215.40	67.30
(3) + HCC	67.49	210.97	66.65	67.62	211.47	66.63

Enrolled (%): Percentage of profitable enrollees. Profit ($): Maximum potential profit of risk selection. See **?**. Profit (%): Maximum potential profit divided by revenue.