Title: Hybrid Risk Adjustment for Pharmaceutical Benefits

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Hybrid Risk Adjustment for Pharmaceutical Benefits

Abstract

This paper analyses the application of hybrid risk adjustment versus either prospective or concurrent risk adjustment formulae in the context of funding pharmaceutical benefits for the population of an integrated healthcare delivery organization in Catalonia during years 2002 and 2003. We apply a mixed formula and find that a hybrid risk adjustment model increases incentives for efficiency in the provision of low risk individuals at health organizations not only as a whole but also at each internal department compared to only prospective models by reducing within-group variation of drug expenditures.

Keywords: drug expenditure, hybrid risk-adjustment, morbidity, clinical risk groups.

JEL Classification: I18

1. Introduction

Two major trends regarding pharmaceutical expenditure are currently taking place in developed countries. On one hand, generic drugs introduction contribute to a decrease in unit prices. On the other, new expensive and innovative molecules are being approved by drug regulatory agencies. The final impact of this trend is still unknown, although some initial effects are being observed. For example, concentration of pharmaceutical expenditures among most costly consumers is very high. While US top 10% consumers represented 66% of pharmaceutical expenditures in 1996, in 2003 this proportion decreased slightly to 64%, however, spending per person has more than doubled from $1,823 to $3,925 [40].

Such concentration in drug expenditure and in general in health expenditure has strong implications on access and funding of new drugs, raises equity concerns [40] and within the context of private insurance it may promote incentives for risk selection [5], or more importantly in this paper, within the context of social insurance it may make difficult to identify efficient / inefficient areas of a health organizations. However, beyond these facts there are relevant changes in population morbidity and mortality that require adjustment.

Understanding population patterns of drug consumption, costs and morbidity are less usual than required since individual data are divided between different sources in fragmented health care systems. However recent research shows the link between prescription drug expenditures and population demographics [21,16].

When citizens are covered under universal coverage and public funding, there is a need for tools to allocate resources for drug expenditures at a population level, which attempt to get value for money. In such situation, understanding morbidity becomes a key issue.

Several initiatives have been developed for setting prescription drugs budgets in primary care, including the addition of incentives [24] and understanding of its variation [13,14,16]. However, prescription drug budget affects all levels of care and not only primary care. The right approach should therefore allow for resource allocation at a population level including all types of drug expenditures.

Under the term risk-adjustment there are several approaches aimed at explaining and predicting costs and utilization of the population using health status data. These models are potentially useful in order to compensate insurers and providers according to the risk they take as reviewed in the literature applied for drugs in the United States [37] or Spain [11]. Risk adjustment has also been used to examine the economic profiling of physicians when claims data are grouped into episodes of care [29]. Most of risk adjustment studies refer to the US population. However, different papers analyze the experience in the application of prospective risk adjustment capitation payments in different countries as Australia [1], or others in Europe [33] as Belgium [27], the Netherlands [19], Germany [4], Switzerland [2], and Israel [28] using of different information sets, as demographic information or diagnosis information. A wide review on the literature and evolution of risk adjustment can be found in Van de Ven and Ellis (2000) [34] .

In health care payment systems design and within a private health insurance/provision system, any resource allocation has to solve the crucial trade-off between efficiency and selection [22,32] depending on the information used in the configuration of the reimbursement scheme. Thus, if we include in the risk adjustment formula only ex ante individual information, which means that the reimbursement is fixed under a prospective risk adjustment scheme, we promote incentives for efficiency because health plans can benefit of the savings in the cut of drug expenditures. However, under prospective payments, health plans may also benefit from selecting patients or benefits. Differently, if we include only ex post individual information in the payment formula, we reduce the risk assumed by health plans, and therefore the incentives for risk selection, although also the incentives for efficiency. When those models use ex post information on cost instead of other indicators of need, they belong to what has been called in the literature a risk sharing formula [30,31,35], while when they use ex post information on diagnosis, they present a concurrent risk adjustment scheme [34].

However, results in terms of incentives for efficiency and risk selection are sensitive to the type of information used in the payment system and depend on the specific environment. Thus, risk selection practices are expected to be less relevant when universal coverage is effective since all patients have access to health care, as happens in our sample, from a population under a

National Health System. In such case, resource allocation requires adjustment for morbidity since this is a key factor on expenditures.

The use of a mixed payment system for total health expenditures started to be explored in the literature in the last decades [3,9,18]. However, there is a relatively new literature addressing specifically the predictability of drug expenditures [37,38,39] and the use of a mixed or hybrid risk adjustment formula with both prospective and concurrent information with the aim of maximizing incentives for efficiency while minimizing incentives for risk selection [8,20]. It is important to note that those risk adjustment strategies are useful even when risk selection is not an issue. There is an analogous problem to risk selection in the context of public provision. The key point is that health institutions receive a budget from health authorities, and risk adjustment allows for the identification of efficient and inefficient departments of the same health institution, and thus, may avoid a scheme of cross subsidies from the efficient to the inefficient departments. When risk adjustment is not used, differently, the budget of the health institution is considered as a whole and there are no incentives for efficiency within the different departments of the organization, promoting free-riding in the inefficient departments. In a former article [11], we have shown the extent of predictability of pharmaceutical expenditure according to morbidity grouped with the use of the Clinical Risk Groups classification system under different specification models applying risk adjustment (and compared our results to other articles in the literature). A recent comparison of the different information systems has been provided by the Society of Actuaries [36].

In this article, we use individual data and analyze the relationship between drug expenditures and morbidity for the population belonging to an integrated healthcare organization covered by the public health system in Catalonia, in the context of the Spanish National Health System. We present this analysis specifically for drug expenditures given the increasing importance of drug expenditures in the total budget of health expenditures in countries such as Spain, where pharmaceuticals accounted for 22.9% of total health expenditures in 2005, compared to 19.2% in 1995 [23]. Budget allocation needs to take into account legitimate differences in cost according to morbidity. Integrated healthcare systems are increasingly searching for tools to allocate budgets and set the right incentives for health benefits. Thus, the use of a hybrid

formula in the allocation of budgets allows for the use of concurrent information for patients with specific conditions which tend to concentrate drug expenditures benefits from its higher predictive power and compensates deviations in drug expenditures which are explained by morbidity.

2. Data Sources

We use individual data on prescription drug consumption and morbidity from an integrated healthcare organization, Serveis Sanitaris Integrats del Baix Empordà (SSIBE), in Catalonia. The organization provides publicly funded health services (hospital care, primary care, and long-term care) to the population in the county of Baix Empordà. SSIBE is responsible to internally allocate the budget stemming from public funds received from the Catalonian public health authority in order to provide the health services provision in the county. The providers taken into account are: Palamós Hospital, which has 100 beds for acute patients and 50 for skilled nursing care, and 4 Primary Care Centers. The database includes all ambulatory pharmacy benefits for the population. Although citizens may also receive specialized benefits outside the organization, the data on benefits and costs from outside the organization were unavailable.

SSIBE has an information system that integrates clinical activities and costs. The main features that define this information system are: (1) unique identification patient files for all encounters (primary care, specialized care, and inpatient services) and (2) decentralized activity file codified in ICD-9-CM by clinicians and reviewed by documentalists. The identification of each encounter allows the costs allocation, as in our case, pharmacy costs.

This research uses the following anonymized databases belonging to years 2002 and 2003: population database, encounters database, and pharmacy database. The first population database was created with the information relative to all the resident population in Baix Empordà: 116,936 citizens. This paper is based only on the analysis of 4 Health Basic Areas (ABS) managed by SSIBE and it refers to morbidity and pharmaceutical expenditure of 87,436 members who were covered during years 2002 and 2003 by the integrated delivery system.

Morbidity measurement is performed by the aggregation of the information on codified encounters of the population with the organization (1,290,642 diagnosis and procedures codes). Among the possible risk adjustment systems, in this article we use the *Clinical Risk Groups* (CRGs) (version 1.2B) which allows classifying individuals in mutually exclusive categories while preserving clinical significance, and taking into account co-morbidities and severity levels [15,17]. From the three different models provided by the CRG software, we use the concurrent model.

For each patient we get a unique CRG as well as its corresponding aggregation in ACRG1, ACRG2 and ACRG3. In this paper we describe the population through the highest level of aggregation (ACRG3) and for the estimations we use the second level of aggregation ACRG2 for the classification of patients in morbidity groups. This level of aggregation originally has 176 mutually exclusive categories. However we slightly modify those into 82 mutually exclusive categories fully maintaining its clinical significance by joining patients belonging to different CRGs of the same category but with different levels of severity, in order to avoid over fitting in our estimation because of a very low number of patients in some groups.

Pharmaceutical expenditure information refers both to prescriptions provided by pharmacists publicly financed by Servei Català de Salut (CatSalut) and to prescriptions to inpatients and medical ambulatory supply to ambulatory patients. Therefore, we include in the analysis ambulatory pharmaceutical prescriptions by the doctors belonging to SSIBE and billed by pharmacists, but also primary care, and specialized care prescriptions; and the total pharmaceutical expenditure includes both public financing and private copayment (with a total of 1,206,008 primary care prescriptions that sum up 14,028,102€ in year 2002). This consumption information incorporates residents as well as other persons that received services from SSIBE. Also it includes resident people with charge to international agreements or people whom they have provisional authentication codes. This means that the total pharmaceutical consumption in the region cannot be fully allocated because part of this consumption does not correspond with the resident's file. Finally, pharmaceuticals consumers in 2002 were 50,280 (57.5 % of the population) with a total individually allocated expenditures of 13,026,913€, from which there is a primary care prescriptions expenditure of 12,091,603€ and a hospital

expenditure of 935,310€. Pharmaceutical consumption corresponding to prescriptions beyond SSIBE physicians or OTC drugs was not available.

Table 1 provides the descriptive statistics of the sample. The population is almost equally distributed between males (50.53%) and females (49.47%), and the average pharmaceutical cost has increased from 148.94 euros in 2002 to 182.68 euros in 2003, with 42.50% in 2002 and 38.64% of the population having zero drug expenditure. From table 2, we also observe how most of the patients belong to the healthy condition under the most aggregated classification system (65342 patients representing 74.73% of the sample in 2002 and 63958 patients representing 73.15% of the sample in 2003) while only a few belong to the highest severity group which classifies to the catastrophic condition (125 patients representing 0.14% of the sample in 2002 and 135 patients representing 0.15% of the sample in 2003). From the subgroup of patients with zero drug expenditures, most of them, 95% are classified as healthy (35,421 out of 37,162 in 2002 and 32,397 out of 33,788 in 2003).

3. Study design

This paper estimates prospective, concurrent, and hybrid models using different information sets in order to predict drug expenditures in the subsequent year. Our objective is to examine the predictive power of each model, how well they explain future cost, and provide implications in terms of the application of a hybrid payment formula in the incentives of efficiency and risk selection in the pharmaceutical market. The basic model is provided by:

$$DrugExp_{i,t} = f(demo_{i,t-1}, HS_{i,t-1,t}, \varepsilon_{i,t})$$

Thus, the dependent variable, drug expenditures in year *t* for individual *i*, is explained by some independent variables or risk adjusters (individual demographic characteristics and health status information). Demographic information is provided by twelve age-gender cells. Prospective risk adjustment models predict actual drug expenditure with information on demographic characteristics and clinical status condition in year *t-1*. Differently, concurrent risk adjustment models predict actual drug expenditure using demographic and actual information on clinical status. As a consequence, given the actual information, concurrent risk adjustment models explain a higher proportion of the variation in health expenditures than prospective risk

adjustment models [34]. However, they do not solve the problem of identifying the efficient and inefficient departments of the health institution stemming from the asymmetry in the information used by health authorities and providers at each department of the institution. Thus concurrent formulae using information posterior to the enrollment, do not avoid the configuration of cross subsidies among departments and therefore reduce incentives for efficiency. If we had a perfect capitation formula in order to set up prospective reimbursement [32] to each different department of the health institution, expected costs per individual would equal expected reimbursement so that we would solve at the same time the problems of incentives for efficiency at each department and at the health institution as a whole. Unfortunately there is a consensus in the literature that a perfect capitation formula can not be reached [34].

Hybrid risk adjustment models combine both prospective and concurrent models. Pure prospective models promote incentives for efficiency but they are unable to avoid free-riding among departments of the same institution. Differently, the use of concurrent reimbursement models, as those based on actual information on cost within the risk sharing strategies, presents lower incentives for free-riding within departments because payment or budget for each department is associated to its actual information, but incentives for efficiency are also reduced when using actual information on costs. The use of diagnosis-based risk adjustment models does not solve the problem of free-riding because they do not capture within-condition variation even with concurrent information [10]. Therefore, we propose the use of a hybrid risk adjustment model with information on health conditions different to the classification system used in the risk adjustment model, trying to rescue the positive properties of both prospective and concurrent formulae. Hence, we need to divide population into two types. The health provider will receive a prospective reimbursement for the first types, while the reimbursement associated to the second type of patients under the hybrid systems is set as a concurrent payment. The division of the population has to be such that the set of individuals composing the prospective reimbursement are those for whom health care provision is not expect to suffer free-riding from other departments, with directly assigned expenditures. Differently we would like to have in the population receiving the concurrent payment to those patients whose provision is at risk of suffering free-riding from other departments within the health institution. In order to

obtain results comparable with the related literature, we utilize the set of 100 verifiable, expensive, predictive conditions (VEP100) that has been presented in Dudley et al. (2003) [8]. As an example, the first five VEP conditions used in the literature are anoxic brain damage, stomach cancer, AMI, leukemia, and peritonitis; and also belong to this list of conditions other types of cancer or HIV. The appropriateness of those conditions stems from the fact that being verifiable (based on objective clinical measures) it is avoided the risk of classifying to this set of patients simply to any expensive patient; being expensive and predictive we select the type of patients whose provision might be at risk of suffering free-riding within departments in the same health institution because of for example, long term treatments.

Because the set of VEP100 conditions in our sample might be different from that of the U.S. in the literature, we checked its validity by comparing the relative cost weights of the set of patients with and without VEP100 conditions presented in table 1. As expected, patients suffering at least one of the specific VEP100 conditions systematically present drug expenditures much higher than the rest of patients (603€ versus 92€ in 2002 and 724€ versus 106€ in 2003). Because the problem of risk adjustment models is due to the within-group variation in expected expenditures, we check the distribution of the appearance of VEP100 conditions under the CRG classification system. In table 2 we observe how in relative terms, 96% of healthy patients do not suffer any VEP100 conditions, while increasing the level of severity in the CRGs supposes increase also the proportion of patients with at least one VEP100 condition until around 97% of patients in the catastrophic conditions group. However, it is important to note that in absolute terms about 23% of all patients suffering at least one VEP100 condition (2,165 out of 9,629 in 2002 and 2,473 out of 10,730 in 2003) belong to the healthy group promoting incentives for risk selection. Therefore, we utilize the same VEP100 conditions classification which allows also comparison with other works in the literature.

In this article, the specification used in the estimations is the linear regression since although other specifications are considered in an earlier work [11], they do not significantly increase the predictive power while linear regression keeps simplicity in the interpretation for health policy makers. Other alternatives are also being explored in the risk adjustment literature, as the use of regression tree boosting to risk adjust health care cost predictions [29]. The methodology

proposed in this paper, however, differs from other studies in three important specificities. First, we provide a first approach for a sensitivity test in the use of hybrid risk adjustment, through the use of two different divisions of the population, suffering first at least one of the VEP100 conditions, and second, suffering more than one of the VEP100 conditions. The second difference with other approaches in the literature is the use of CRG instead of DCG as the patient classification system. Until now studies on hybrid models had not used the clinical categories in the risk adjustment models. Finally, this is the first analysis of this type examining hybrid risk adjustment strategies for a subset of the Spanish population, under a National Health System.

4. Main findings

Demographic information only allows an explained variation of drug expenditures of 9% (Model 1, R^2= 0.09) (Table 3). However, including health status information in the prospective model (models 2), the predictive power increases until R^2 = 0.21 (only CRG information in model 2a), 0.24 (demographic and CRG information in model 2b) and 0.27 (demographic, CRG information, and presence of at least one VEP100 condition in model 2c). Thus, the higher is the quality of the information used in the prospective model, the better is the predictive power, and including a dummy variable with the presence of a VEP100 condition improves the usual prospective model of the usual risk adjustment model that uses the CRG classification system. Concurrent models 3a to 3c (using only CRG information, demographic and CRGs, or demographic, CRGs and presence of VEP100 conditions respectively) behaves equally and increases the proportion of explained variance to a highest value of R^2=0.2893 (model 3c). When dividing population into two parts depending upon the presence of at least one VEP100 condition, the R^2 in the prospective models for patients without those conditions increases and is similar to that of the concurrent model for the whole population, with an R^2 of 0.2769 (model 5c). The reason is that we have eliminated from that sample patients suffering VEP100 conditions (12.27% of the sample), who present a high variation of drug expenditures within CRG categories. At the same time, even in concurrent models, the R^2 of models for those patients with high variation in drug expenditures decreases to 0.2099 (model 4c). The hybrid

models take into account the two sub-samples with concurrent information for patients with at least one VEP100 condition and prospective information for patients with no VEP100 condition. In order to calculate the R^2 for hybrid models, we first calculate the total error sum of squares for the combined populations (concurrent and prospective) as the error sum of squares for the concurrent population plus the error sum of squares from the prospective population. At the same time, the corrected total sum of squares is calculated as the sum of squares adjusted for the mean of the overall population. Finally, the R^2 is defined as one minus the ratio of the error sum of squares to the corrected total sum of squares. This methodology has been previously used in the literature [8]. We obtain an R^2 for hybrid models of 0.2263 (model 6c), which is similar to the predictive power of the usual prospective model using demographic and health status information (model 2b) but in which efficiency incentives are higher for provision of pharmaceutical products for 87.73% of the population, and there are no incentives for risk selection for the provision of pharmaceutical products in those patients with VEP100 conditions who are thought to be at risk of suffering risk selection.

In a further attempt to check the validity of the hybrid risk adjustment model, we proceed to develop a sensitivity analysis by changing the criteria for the division of the population. Thus, models 7 to 9 are similar to models 4 to 6, but in which the prospective risk adjustment is assigned for patients suffering less than two VEP100 conditions (96.98%), and the concurrent risk adjustment for patients with at least two VEP100 conditions (3.02%). In this model, the efficiency incentives remain for a higher proportion of the population, but the predictive power in the prospective model decreases to an R^2 of 0.2199 (model 8c) because we have included patients with high variation in drug expenditures within CRG categories in the sub-sample. Therefore, there still exist incentives for risk selection in this hybrid model for patients suffering one VEP100 condition. Differently, the predictive power of the concurrent model for those patients with more than one VEP100 conditions hugely increases (R^2 of 0.3185 in model 7c), and the R^2 of hybrid models remains in the same level (R^2 of 0.2395 in model 9c versus an R^2 of 0.2263 in model 6c). The interpretation of this result is that the free variation in drug expenditures is specially concentrated in patients suffering one VEP100 conditions because most of them still belong to relatively healthy CRG categories. It is important to note that our R^2

are probably higher than should be expected in other national samples in that all of the providers are from a narrow geographic area, and hence drug expenditure and practice style variations are reduced compared to other greater national samples.

Table 4 presents the predictive ratios for the different risk adjustment models and by different groups of population. In the validating sample, the proportion of population with and without VEP100 conditions slightly varies (12.39% have at least one VEP100 condition and 3.05% have more than one). Results support those from the R^2 presented. All models (prospective, concurrent, and hybrid) benefits from including a dummy variable with the presence of VEP100 conditions. Hybrid models improve the predictive ratio for patients in most of CRG categories, but especially when patients are ordered by deciles of drug expenditures or by presence of VEP100 conditions. Also, the importance of prevalence of clinical conditions is evidenced by the fact that for patients at some CRG categories, prospective models present a better predictive ratio (closer to 1) than concurrent models, which is explained by the timing of the diagnosis during the natural year.

5. Conclusions

Development of mixed models of resource allocation, prospective and concurrent at the same time, is a goal for publicly and privately funded health systems. Although risk adjustment models contribute to such goal, specific mechanisms have to be defined. In this paper we follow a hybrid risk adjustment approach in the literature which proposes to divide population into two groups. We utilize the VEP100 set of verifiable, expensive, predictive conditions used in the literature to split the population. We include the presence of those conditions as a risk adjuster in the prospective and concurrent models because they explain at some extent the high variation in drug expenditures within groups. Although it is not shown here or elsewhere that this is the optimal way of dividing population, in this paper we show how resource allocation can be improved in the delivery of pharmaceutical benefits for the population in a county in Catalonia served by an integrated healthcare organization. Such system can be applied to similar organizations and a “yardstick competition” model could be applied.

The prospective models showed here present a high predictive power. However, the hybrid models improve the predictive power for patients whose health provision is at risk of suffering free-riding through cross subsidies from efficient to inefficient departments of the health institution. Risk adjustment allows for a better identification of the efficiency in the different departments, and hybrid risk adjustment limits the increase in the financial risk of the efficient departments given unexpected changes in the morbidity of the population. The procedure is based on the concurrent part of the reimbursement formula to fixed amounts according to the verifiable presence of some expensive conditions, and compensates deviations in drug expenditures which are explained by morbidity given its high variation within groups. In such a situation there is a risk of up-coding, although this behavior could be addressed through targeted auditing. In this research we have taken the VEP conditions as given. However, we understand that there is a need to define specific VEP conditions for pharmaceutical expenditure since their impact in pharmaceutical expenditure might be different than that in total health expenditure. Future research is needed towards the application of hybrid risk adjustment models comparable to other studies in the literature and with respect to the search of the optimal set of specific conditions in specific environments that solves the tradeoff between efficiency in the entire health institution and for each department of the institution avoiding free-riding at a minimal cost. Pharmaceutical expenditure is only one part of total expenditures. Therefore, we understand that an application focusing on total expenditures for health benefits package is the next research approach that is needed.

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Table 1: Descriptive statistics of the sample. N=87436 and relative cost weights by the presence of Verifiable Expensive Predictive (VEP100) conditions.

Gender	**Number**	**Proportion**
Males	44181	50.53%
Females	43255	49.47%
	Average	Std. Deviation
Age	39.13	22.64

	2002			2003		
Average pharmacy cost	148.94			182.68		
Presence of VEP100 Conditions	**Mean Annual Cost**	**Mean Annual Relative Cost Weight**	**Sum patients**	**Mean Annual Cost**	**Mean Annual Relative Cost Weight**	**Sum patients**
Patients with no VEP100 conditions	92.73	0.62	77807 (88.98%)	106.83	0.58	76706 (87.72%)
Patients with at least one VEP100 condition	603.05	4.05	9629 (11.02%)	724.85	3.97	10730 (12.28%)
all patients	148.93	1.00	87436 (100%)	182.67	1.00	87436 (100%)

Table 2: Distribution of health conditions and presence of VEP100 in patients.

Health conditions by Clinical Risk Groups (highest level of aggregation)	Patients with no VEP100 in 2002		Patients with at least one VEP100 in 2002		Patients with no VEP100 in 2003		Patients with at least one VEP100 in 2003	
	N	% by CRG	N	% by CRG	N	% by CRG	N	% by CRG
Healthy	63177	96.69	2165	3.31	61485	96.13	2473	3.87
History Of Significant Acute Disease	5364	79.00	1426	21.00	5538	76.11	1738	23.89
Single Minor Chronic Disease	3384	87.87	467	12.13	3783	88.84	475	11.16
Minor Chronic Disease In Multiple Organ Systems	371	77.45	108	22.55	439	82.99	90	17.01
Single Dominant Or Moderate Chronic Disease	4555	58.45	3238	41.55	4522	55.93	3563	44.07
Significant Chronic Disease In Multiple Organ Systems	932	34.98	1732	65.02	918	33.10	1855	66.90
Dominant Chronic Disease In Three Or More Organ Systems	17	10.06	152	89.94	13	6.99	173	93.01
Dominant, Metastatic, And Complicated Malignancies	3	1.35	220	98.65	4	1.69	232	98.31
Catastrophic Conditions	4	3.20	121	96.80	4	2.96	131	97.04

Table 3: R-squared of the different risk adjustment models

Predictors	R-squared	Percentage of patients	Timing	N	Number of parameters
Model using only demographic information					
M1: Only demographic information	0.0905	100.00%	Prospective	87436	12
Prospective models including diagnostic and procedures information					
M2a: Only information on CRG conditions	0.2187	100.00%	Prospective	87436	82
M2b: Demographic and CRG conditions information	0.2458	100.00%	Prospective	87436	94
M2c: Demographic, CRG and existence of VEP100 information	0.2783	100.00%	Prospective	87436	194
Concurrent models including diagnostic and procedures information					
M3a: Only information on CRG conditions	0.2253	100.00%	Concurrent	87436	82
M3b: Demographic and CRG conditions information	0.2506	100.00%	Concurrent	87436	94
M3c: Demographic, CRG and existence of VEP100 information	0.2893	100.00%	Concurrent	87436	194
Dividing the sample between those with and without VEP100 in 2003					
M4a: Only information on CRG conditions	0.1480	12.27%	Concurrent	10730	82
M4b: Demographic and CRG conditions information	0.1616	12.27%	Concurrent	10730	94
M4c: Demographic, CRG and VEP information	0.2099	12.27%	Concurrent	10730	194
M5a: Only information on CRG conditions	0.1886	87.73%	Prospective	76706	82
M5b: Demographic and CRG conditions information	0.2535	87.73%	Prospective	76706	94
M5c: Demographic, CRG and VEP information	0.2769	87.73%	Prospective	76706	194
M6a: Hybrid Model (concurrent m4a for 12.27 and prospective m5a for 87.73%)	0.1579	87.73%+12.27%	Hybrid	87436	82
M6b: Hybrid Model (concurrent m4b for 12.27% and prospective m5b for 87.73%)	0.1841	87.73%+12.27%	Hybrid	87436	94
M6c: Hybrid Model (concurrent m4c for 12.27% and prospective m5c for 87.73%)	0.2263	87.73%+12.27%	Hybrid	87436	194
Dividing the sample between those with one or none VEP100 and those with at least two VEP100 in 2003					
M7a: Only information on CRG conditions	0.2084	3.02%	Concurrent	2640	82
M7b: Demographic and CRG conditions information	0.2193	3.02%	Concurrent	2640	94
M7c: Demographic, CRG and VEP information	0.3185	3.02%	Concurrent	2640	194
M8a: Only information on CRG conditions	0.1681	96.98%	Prospective	84796	82
M8b: Demographic and CRG conditions information	0.1982	96.98%	Prospective	84796	94
M8c: Demographic, CRG and VEP information	0.2199	96.98%	Prospective	84796	194
M9a: Hybrid Model (concurrent m7a for 3.02% and prospective m8a for 96.98%)	0.1761	96.98%+3.02%	Hybrid	87436	82
M9b: Hybrid Model (concurrent m7b for 3.02% and prospective m8b for 96.98%)	0.2023	96.98%+3.02%	Hybrid	87436	94
M9c: Hybrid Model (concurrent m7c for 3.02% and prospective m8c for 96.98%)	0.2395	96.98%+3.02%	Hybrid	87436	194

Table 4: Predictive Ratios for the different risk adjustment models

		Prospective models			Concurrent models		Hybrid models dividing patients with and without VEP100 in 2003		Hybrid models dividing patients with 0 or 1, and those with at least two VEP100 in 2003	
	N from validating subsample of 43416	M1: Only demographic information	M2b: Demographic and CRG conditions information	M2c: Demographic, CRG and VEP100 information	M3b: Demographic and CRG conditions information	M3c: Demographic, CRG and VEP100 information	M6b: Hybrid Model (concurrent m4b for 12.39% and prospective m5b for 87.61%)	M6d: Hybrid Model (concurrent m4c for 12.39% and prospective m5c for 87.61%)	M9b: Hybrid Model (concurrent m7b for 3.05% and prospective m8b for 96.95%)	M9d: Hybrid Model (concurrent m7c for 3.05% and prospective m8c for 96.95%)
Predictive Ratios by health conditions in 2003										
Healthy	32547	1.8516	0.9416	0.9423	1.2606	1.2242	1.0730	1.0516	0.9750	0.9740
History Of Significant Acute Disease	3338	0.8333	1.1218	1.1333	0.9850	0.9858	1.0301	1.0153	1.1353	1.1414
Single Minor Chronic Disease	1905	0.9179	0.9844	0.9828	0.9313	0.9153	1.0429	1.0198	1.0101	1.0135
Minor Chronic Disease In Multiple Organ Systems	232	0.8046	1.2132	1.2062	0.9295	1.0080	1.2065	1.2916	1.1707	1.1778
Single Dominant Or Moderate Chronic Disease	3870	0.6292	0.9970	0.9934	0.8519	0.8658	0.9616	0.9714	1.0009	1.0035
Significant Chronic Disease In Multiple Organ Systems	1275	0.4729	0.9783	0.9769	0.7837	0.8063	0.8907	0.8832	0.9399	0.9395
Dominant Chronic Disease In Three Or More Organ Systems	89	0.3155	0.9201	0.9677	0.6741	0.7186	0.7674	0.7815	0.8349	0.8645
Dominant, Metastatic, And Complicated Malignancies	101	0.3321	0.6679	0.6940	0.5728	0.5636	0.6099	0.5828	0.5703	0.5531
Catastrophic Conditions	59	0.0389	1.1060	0.9949	0.7480	0.7202	0.8082	0.7859	0.9617	0.9390
Predictive Ratios by deciles of drug expenditures in 2003										
decile 1 to 5	21782	98.3804	48.5114	47.1167	39.3490	37.7547	44.1155	42.9303	46.5413	45.7752
decile 6	4313	5.6628	5.5222	5.3143	5.8729	5.5279	5.0550	4.7754	5.3420	5.1908
decile 7	4348	3.2237	3.4102	3.2960	3.5795	3.3922	3.2857	3.1337	3.3608	3.2837
decile 8	4369	1.9669	2.1467	2.0881	2.2648	2.1726	2.1208	2.0403	2.1061	2.0471
decile 9	4333	1.0562	1.2088	1.1731	1.2506	1.2123	1.2379	1.1950	1.2195	1.1880
decile 10	4271	0.3301	0.4863	0.5086	0.4894	0.5175	0.5096	0.5291	0.4999	0.5213
Predictive Ratios by VEP100 procedures										
no VEP100 in 2003	38142	1.5202	1.2262	1.1770	1.1110	1.0197	1.0154	1.0130	1.1599	1.1266
at least one VEP100 in 2003	5274	0.4703	0.7406	0.7858	0.8440	0.9294	0.9563	0.9421	0.8093	0.8454
zero or one VEP100 in 2003	42118	1.1630	1.0703	1.0509	1.0328	0.9951	1.0259	1.0013	1.0050	1.0025
At least two VEP100 in 2003	1298	0.3777	0.6608	0.7237	0.7703	0.8972	0.8295	0.8865	0.9196	0.9333