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Addressing Market Segmentation and Incentives for Risk Selection: How Well Does Risk Equalisation in the Irish Private Health Insurance Market Work?

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Abstract: This study assesses the efficacy of Ireland's recently introduced risk equalisation scheme in its voluntary health insurance market. Robust risk equalisation is especially important in an Irish context given acute risk segmentation and incentives for risk selection that have evolved within the market. Using uniquely acquired VHI data (N=1,235,922) this analysis assesses the predictive efficacy of both current and alternative risk equalisation specifications. Results suggest that the low predictive power of the current risk equalisation design (R^2 = 6.8 per cent) is not appropriately correcting for anti-competitive incentives and asymmetries in the market. Improvements to the current design could be achieved through the introduction of diagnosis-based risk adjusters.

I INTRODUCTION

Community rating, which limits the extent insurers can vary premiums based on insurees' risk profiles, is a key feature of many health insurance markets. While promoting equity, this regulation incentivises insurers to focus on attracting low-risk (profitable) consumers while avoiding high-risk (unprofitable) consumers, a phenomenon known as risk selection. Risk selection has a number of negative

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consequences; potentially resulting in market segmentation, poor quality service to high-risks (e.g. old and sick), and/or a welfare loss as investment is focussed on attracting low-risks (e.g. young and healthy) rather than price and quality competition (van de Ven, 2011; van de Ven and Ellis, 2000). The best strategy for reducing risk selection incentives has been identified as good risk adjustment (van de Ven and Ellis, 2000). Commonly, this involves providing risk-adjusted premia subsidies to insurers based on insurees' risk profiles, thereby equalising the risks different insurees represent. These subsidies are then generally administered through what is known as a risk equalisation (RE) scheme (van de Ven, 2011).

Risk equalisation is a common feature of many community-rated competitive health insurance markets internationally (see, Breyer *et al.*, 2012). However, the Irish market evolved largely without the allocation of risk-adjusted subsidies between insurers. This raised important policy concerns as it created strong incentives for risk selection and contributed to acute market segmentation which has undermined community rating regulations (Turner and Shinnick, 2013; Armstrong, 2010).

Risk equalisation payments have been in operation since 2013, yet lack of access to individual-level claims data has made analysis of the efficacy of the current risk equalisation design difficult. Recently, Keegan *et al.* showed that the current Irish RE design substantially reduced cost differentials between switchers and stayers, although perhaps not completely eliminating them (Keegan *et al.*, 2015). Yet a more detailed statistical analysis examining the ability of RE to predict healthcare expenditures, a common benchmark of performance internationally (Breyer *et al.*, 2012), has yet to take place.

Understanding the strength of the current RE design may also help inform debate over future health financing reform. While recent plans to expand from a voluntary to mandatory health insurance system (DOH, 2014a) have been abandoned on cost grounds (Wren *et al.*, 2015; KPMG, 2015), there was a lack of evidence on the competitive foundations for such a transition. In this context, robust RE is considered a crucial precondition for insurer competition in mandatory health insurance markets (Bevan and van de Ven, 2010; Thomson *et al.*, 2013).

The focus of this paper, therefore, is to use individual-level claims expenditure data to empirically examine the predictive efficacy of the current Irish RE design against a number of other alternatives. Of particular interest is the role diagnostic information may play in improving risk equalisation performance. Basing RE payments on diagnostic information collected from administrative data is a feature of more sophisticated RE designs internationally (Breyer *et al.*, 2012).

Section II provides an overview of voluntary private health insurance (VPHI) in Ireland, including a background to RE. Section III describes the data and methods and Section IV presents the results. Section V discusses the implication of these findings. Section VI concludes.

II PRIVATE HEALTH INSURANCE IN IRELAND

The Irish health system is predominantly tax-financed (71 per cent). Hospital-based expenditure represents the largest category of financing both publicly and in terms of private health insurance (CSO, 2015). Eligibility for tax-financed care is complex (Thomson *et al.*, 2012). However, the defining feature of eligibility is that all are entitled to publicly-funded acute hospital care, although some individuals are required to pay a daily charge.[1]

Despite this entitlement, approximately 43.9 per cent of the population currently avail of VPHI cover (HIA, 2014a).[2] The main benefits of VPHI relate to its supplementary role, particularly faster access to elective hospital care. VPHI mainly covers costs for hospital-based care with only partial reimbursement for outpatient and primary care expenses. VPHI has been described as "playing a key social role" through easing pressure on the public health system and maintaining access to health services (Columbo and Tapay, 2004). As such there has traditionally been strong policy commitment to promoting VPHI. Tax relief is granted on private health insurance at a standard rate of 20 per cent (deducted at source by the insurers) while, historically, the State has charged private health insurers below the full economic cost of care in public hospitals. State subsidisation also takes place more indirectly through the training of private medical staff by the public system (Nolan, 2006). State promotion of VPHI, however, has proved controversial (Nolan, 2006). A particular controversial aspect of VPHI provision is that much of the care takes place in public hospitals. As such, not only do wealthier and healthier privately insured individuals (Kiil, 2012) receive faster access to elective hospital care, but in many instances they do so in public hospitals, "crowding out" access to public patients (Smith and Normand, 2009).

In recent years, however, there has been a partial unwinding of state support for VPHI. For instance, since 16 October 2013, the premium amount on which standard tax-relief is granted has been capped at €1,000 for each adult and €500 for each child and student. In addition, charges for private care in public hospitals have increased substantially to better reflect the economic cost of care (Turner, 2015).

VPHI has been available in Ireland since 1957, where it was solely provided by the state-backed Voluntary Health Insurance Board (now trading as Vhi Healthcare) (VHI). However, due to EU mandate, the market was liberalised in the mid-1990s and is now populated by four competing insurers,[3] of which the VHI

[1] This daily charge is currently set at €75 per day for in-patient and day-patient services, capped at a maximum of €750 in any 12 consecutive months (Citizens Information, 2014).

[2] This figure does not capture any effect lifetime community rating, introduced in May 2015, may have had on insurance take-up.

[3] However, on March 9, Irish Life announced agreements to acquire Aviva Health, take full ownership of Glo Health, and to merge the two companies (HIA, 2015b).

still has the largest market share (HIA, 2014b). The market is heavily regulated. Historically, operating under the principles of intergenerational solidarity, the market has been defined by single-rate community rating regulations, whereby insurers were required to charge all individuals the same premium per plan (subject to some exemptions for children and full-time students). However, as of May 2015, lifetime community rating regulations now apply. Specifically, a loading of 2 per cent of gross premium now applies for those aged 35 and over for every additional year they postpone purchase of inpatient private health insurance (up to a maximum loading of 70 per cent and subject to some exemptions, see HIA, 2015a). The market is also subject to open enrolment, lifetime cover and minimum benefit regulations.

2.1 Risk Selection and Market Segmentation

Despite the market being subject to community rating, RE was slow to develop. Particularly, efforts to commence RE payments in 2006 were successfully challenged by the first market competitor (BUPA) (Turner and Shinnick, 2013). This had profound effects on the evolution of the market from a competitive perspective. Following liberalisation, there was a strong shift in new and existing consumers, generally the younger and healthier, away from the incumbent VHI and towards the newer entrants. Lack of RE made it difficult for the VHI to compete on price, perpetuating this market segmentation and undermining the principle of community rating (Turner and Shinnick, 2013). Evidence from August 2014 shows that while VHI insures 54 per cent of the VPHI market overall, 87 per cent of all policyholders aged 80 years and over, are insured with the VHI (HIA, 2014b).

While much of this consumer mobility is likely explained by low-risk consumers naturally experiencing lower switching costs (Duijmelinck *et al.*, 2015), incentives for risk selection were also strong given the absence of RE. In this context, the increase in product proliferation as the market evolved has been considered a sign of insurers looking to segment risk. This includes an increase in policies with large deductibles and reduced benefits (such as orthopaedic benefits) which are less attractive to high risks (HIA, 2014c). Moreover, it is likely newer entrants had greater ability to engage in risk selection activities. For example, newer entrants have tended not to have branch offices which may dissuade older individuals from contracting with them (Armstrong, 2010). In addition, newer entrants have been shown to have likely engaged in "price-shadowing" strategies, setting prices slightly below similar VHI plans, in an effort to attract more price-sensitive, low-risk individuals (Competition Authority, 2007).

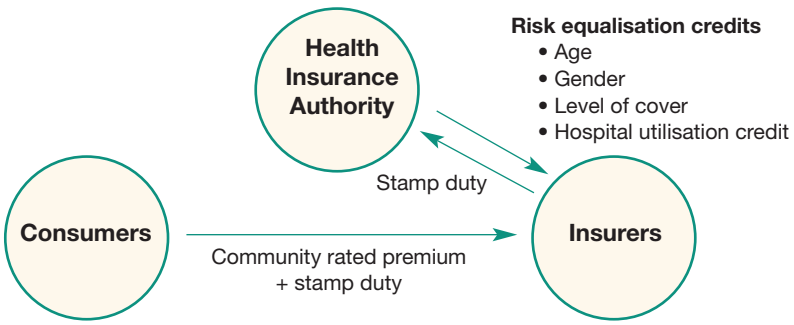
2.2 Age-Related Tax Credits and Bona-Fide Risk Equalisation

Given concerns over these issues an interim scheme was introduced in January 2009. The scheme combined two measures designed to support the cost of health insurance for older people. First, an additional tax relief on health insurance

premiums was introduced for people aged 50 and over and increasing for higher age groups. This tax relief was deductible at source, meaning consumers only paid the net premium after the tax relief was applied to the gross premium set by the insurers. The value of the tax relief was then paid by the Revenue Commissioner to the insurers (DOH, 2008). Secondly, in order to fund this additional tax relief, a new community rating stamp duty was introduced payable by insurers for each individual insured. The stamp duty payable was lower for children than adults, reflecting the lower community-rated premium they pay.

This progressed to a RE scheme in January 2013. The new RE design differs from the interim system in a number of ways. First, RE credits are now payable from a fund operated by the Health Insurance Authority (HIA) rather than in the form of tax credits. Second, although the fund is financed similarly to the interim scheme, based on stamp duties that vary between children and adults, stamp duties also now vary between levels of cover. Those with non-advanced contracts pay a lower stamp duty reflecting their lower expected claims costs. The stamp duty is payable by all open member insurers to the RE fund. Finally, the RE fund reallocates out the proceeds of the stamp duty to competing insurers in the form of RE credits (HIA, 2013). These credits are paid to insurers based on age-bands of older individuals (60-64, 65-69, 70-74, 75-79, 80-84, 85+), which are further disaggregated by sex and level of policy cover. In addition, a credit is also payable in respect of each night spent in private or semi-private accommodation by an insured person (applicable to all insured individuals). From March 2016 onwards, insurers also receive a payment in respect of each daycase admission. These credits to insurers are termed "risk adjusters" and are prospectively set. That is, insurers know the value of these payments in advance of any claims being incurred. The credits set for each period (usually 12 months) are informed by HIA analysis of detailed policyholder information, including claims and utilisation data, submitted by insurers to the regulator in the previous period (HIA, 2013).[4] The payment flows of this system are captured in Figure 1.

Figure 1: Irish Risk Equalisation Payment Flows



[4] Based on this analysis, and among certain other considerations, the Minister of Health will then decide on amendments to the credits specified (see HIA, 2013).

III DATA AND METHODS

Data for this study were provided by VHI and related to individual-level claims expenditure data for 1,235,922 insured VHI members, covering the years 2010-2012.[5] Available socio-economic data related to age and sex. Policy level characteristics consisted of policy type and number of coverage days per year. Claims data related to the number of daycase and outpatient admissions and the number and length of inpatient admissions, along with associated costs. Clinical data were provided in the form of 35 diagnostic cost categories that were compiled with the aid of clinicians in order to predict high-cost diagnoses for internal VHI analysis. These cost categories were predicated on primary International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM) codes. Table A1 (Appendix) provides a list of these diagnosis groups. These categories were defined in-house by the insurer based on clinical judgement. In addition, a variable flagging whether an individual suffered from a chronic condition was also included in the database. The chronic illness flag was calculated in-house by the insurer and based on Iezzoni *et al.*, ICD-9-CM chronic conditions (Iezzoni *et al.*, 1994).

As is common practice, RE models are evaluated based on their ability to explain claims expenditure variation (Breyer *et al.*, 2012). The more variation explained the less incentive to risk-select. Hospital claims expenditure in this study is predicted using a series of OLS regression models. Although claims expenditure data tend to display skewed distributions, the standard approach in RE literature is to apply ordinary least-square (OLS) regression analysis on untransformed claims expenditure (van de Ven and Ellis, 2000).[6]

As is standard, these models are analysed both concurrently and prospectively. This involved dividing the dataset into concurrent and prospective sub-populations. For the concurrent analyses, all persons with any cover in 2012 were included, i.e., a population of 1,235,922 individuals. For the prospective analysis, anybody with cover in 2011 and cover in 2012 were retained, leaving a prospective population of 1,166,425 individuals (see Table 2). The concurrent analysis used risk adjusters from 2012 to model claims expenditure in 2012. The prospective model used risk adjusters in 2011 to model claims expenditure in 2012. In this regard, RE models are specified as follows:

[5] Data collection took place at a time when the interim age-related tax credit scheme was in place.

[6] OLS tends to perform robustly for large samples and replicates the cell-based approach for calculating premium subsidies used in many jurisdictions (including Ireland) (Ellis, 2007; van de Ven and Ellis, 2000). Furthermore, more complex non-linear models may be less suitable in situations where sample sizes are large and models are required to estimate a large number of parameters (Ellis, 2007).

$$Y_{it} = \alpha + X_{it}\beta + u_{it} \text{ (Concurrent)} \quad (1)$$

where $t = 2012$ and $i = 1{,}235{,}922$

$$Y_{it} = \alpha + X_{it-1}\beta + u_{it} \text{ (Prospective)} \quad (2)$$

where $t = 2012$ and $i = 1{,}166{,}425$

The outcome variable of interest in this analysis, Y, is individual-level yearly claims expenditure payable by the insurer. This relates to inpatient, daycase and outpatient claims expenditure. Independent variables in the model are denoted by X, β are associated parameters, and α is a constant. Errors between observed and predicted values are captured by the disturbance term u. The model is estimated by OLS.

3.1 Models Estimated

In all, five RE models are estimated, both concurrently and prospectively. The risk adjusters (i.e. independent variables) included in these models are outlined below and models are summarised in Table 1. Model 3 contains the same set of adjusters on which insurers are currently reimbursed. The prospective version of this model best captures the design of the current risk equalisation scheme.

3.1.1 Age, Sex and Level of Cover

The most basic risk adjusters used to risk-equalise premiums are based on age and sex. They are easy to collect and monitor, however they are poor predictors of claim expenditure (van de Ven and Ellis, 2000; Ellis, 2007). As noted, RE credits in Ireland are provided to insurers based on the age of enrollees, varying in five-year age bands from age 60 up to 84 and for those 85 and older. These credits also vary based on sex and across two levels of cover – advanced and non-advanced. Non-advanced refers to basic cover policies where "not more than 66 per cent of the full cost of hospital charges in a private hospital or prescribed minimum benefits, if lower, is always provided" (HIA, 2013). Advanced cover refers to all other policies. Level of cover is a unique risk adjuster in an international context. However, its inclusion in the Irish RE model is justified based on the unique public/private mix of hospital care in the Irish system. That is, differences in expenditures between individuals, rather than being a reflection of health status, could represent differences in accommodation (for example, whether a patient was treated in a semi-private ward in a public hospital or private room in a private hospital). As a consequence, insurance products that offer low levels of cover (non-advanced) receive lower RE credits than more comprehensive (advanced) products. Model 1 includes age, sex and level of cover as risk adjusters.

Table 1: Risk Equalisation Models to be Estimated

Model	*Description*
Model 1 Demographic Model	This model consists of 24 (6*2*2) age, sex, non-advanced/advanced cover dummy categories. Where applicable this will be referred to as the demographic model.
Model 2 Demographic Model incl. inpatient nights	Model 1 plus a variable capturing the count of inpatient hospital days per insuree for that year.
Model 3 Model 2 incl. daycase admissions (current RE adjusters)	Model 2 plus a count of daycase admissions. This model is includes the same set of adjusters as the current RE model.
Model 4 Model 2 incl. chronic illness flag	Model 2 plus a binary flag representing whether or not a policyholder received a principal ICD-9-CM diagnosis of a chronic condition within the last two years of interest.
Model 5 Demographic Model incl. diagnostic groups	Model 1 plus 35 count variables representing each aggregated ICD-9-CM diagnostic cost category.

3.1.2 Inpatient Hospital Nights

Models incorporating data on utilisation (or prior expenditures) tend to show significant predictive improvements over models based solely on demographic information (van de Ven and Ellis, 2000). However, the main argument against using utilisation data in RE models is that it creates inappropriate incentives on the part of health insurers as payment of risk-adjusted subsidies is tied directly to quantity of healthcare utilisation. Insurers therefore may not be motivated to pursue cost control. In the absence of information on other measures of health status, the HIA has included a payment for each overnight hospital stay recorded by an insured individual as part of the current RE design. In this context, Model 2 includes age, sex, level of cover and an adjuster for frequency of inpatient hospital stays. The prospective version of this model best reflects the design of the original RE scheme introduced in 2013.

3.1.3 Daycase Admissions

Model 3 supplements Model 2 by including a flag for daycase admissions. As noted, since March 2016 insurers are also reimbursed for each private daycase admission. The prospective version of this model therefore best captures the current RE design.

3.1.4 Diagnostic Information

Using diagnostic information as a measure of health status may help reduce the inefficiency problems associated with reimbursement based on utilisation

information (van de Ven and Ellis, 2000). However, inefficiency incentives may not be completely removed as diagnoses are generally tied to some form of hospitalisation. Measures of diagnostic severity may improve the predictive efficacy of RE models as they may better capture variation in cost above that of generic measures of utilisation. However, basing payments on severity of illness may introduce incentives for insurers (where possible) to influence treatment and diagnoses, and "upcode" patient severity (Ellis, 2007). That said, diagnoses from insurance claims have become the most widely used set of information beyond demographic variables (Ellis, 2007). Most health insurance systems with advanced RE schemes tend to use measures of diagnoses as risk adjusters.

A primary objective of this study, therefore, is to assess whether the current RE specification can be improved through the use of diagnosis-based information. This is assessed through the application of two alternative sets of diagnostic information. In addition to the risk adjusters specified in Model 2, Model 4 includes a binary flag representing whether or not a policyholder received an ICD-9-CM diagnosis of a chronic condition within the last two years of interest. Diagnosis of a chronic illness has previously been considered for inclusion in the Irish RE scheme (HIA, 2013).

Including more detailed diagnostic coding was also considered by the HIA, however there was a lack of support.[7] Disadvantages related to practical difficulties including "the large volume of data generated, the lack of a credible volume of data in each cell… and issues with consistency of data and whether it would promote a bias towards in-patient treatment" (HIA, 2010b). However, recently there has been renewed interest in the applicability of diagnosis-based RE in the Irish market (DOH, 2014b). In this context, Model 5 includes information on 35 high cost diagnostic groups based on ICD-9-CM classification (see Table A1).

3.2 Partial Year Weighting and Validation Approach

In order to avoid under-prediction, partial year enrolees' hospital claims expenditures are adjusted through the following procedure. First, partial-year expenditures are annualised by dividing by the fraction of the year each enrolee was covered. Secondly, in the calculation of unconditional and conditional means, each observation is weighted by the same fraction. As is standard, concurrent (where risk adjusters predict claims expenditure in the same period) and prospective models (where risk adjusters predict claims expenditure in the following period) are reported. To avoid inflated predictive accuracy as a result of over-fitting, a ten-fold cross-validation approach is employed. This process involves randomly splitting the data into k approximately equal parts. For the k^{th} part, models are estimated using the remaining k-1 parts and validated on the k^{th} part. This process is repeated

[7] This related to proposed diagnostic payments based on diagnosis-related groups.

for all values of k. This analysis sets k=10. Previous analyses suggest this number of iterations to be sufficient (Behrend *et al.*, 2007; Mookim and Ellis, 2008). Model evaluation metrics of interest (see below) returned from this process are then averaged and reported.

3.3 Evaluation Metrics

Predictive performance of all models will be assessed both from an individual and group-level perspective. It is important to realise, in this regard, that due to the large amount of random variation in healthcare expenditure and the fact that some predictors of expenditure may not be suitable for RE, that RE models (particularly prospectively) often have poor prediction levels (van de Ven and Ellis, 2000). Individual prediction will be measured in terms of the adjusted r-squared statistic (R^2), by Cummings prediction measure (CPM) and by mean absolute prediction error (MAPE).

R^2 is the standard metric for evaluating RE models. However, one concern levelled at the R^2 metric is that, as it squares prediction errors, it can be overly sensitive to large prediction errors (Cumming *et al.*, 2002). MAPE and CPM on the other hand, consider absolute errors, and therefore weight large and small errors the same. MAPE is defined as the mean of the absolute difference between observed and predicted values. CPM provides a standardisation of this absolute deviation, providing a ratio of mean absolute prediction errors to absolute deviations of observations from the unconditional average. CPM thus can be reported as a proportion ranging from 0 to 1 and, in terms of model fit, is interpreted the same as R^2. MAPE and CPM will always display the same relative ranking of models in terms of performance. Higher R^2, CPM and lower MAPE values signify better model fit, respectively.

Group prediction will be assessed through predictive ratios (PR) for both quintile of expenditure and morbidity status. Morbidity status is proxied by the number of diagnoses assigned to an individual within a given year. The closer the predictive ratio is to 1 (i.e. where observed equals predicted expenditure), the better the model performs for that group.

In order to reduce the influence of outliers on model performance and to simulate the impact of introducing outlier-risk sharing, observed claims expenditures are truncated at €25,000. Although this threshold is arbitrarily chosen, it corresponds approximately with similar thresholds in other jurisdictions (e.g. Netherlands, €20,000 (Breyer *et al.*, 2012); Germany, €20,450 (Breyer *et al.*, 2012); and Australia, AUS$50,000 (Connelly *et al.*, 2010)).

3.4 Sensitivity Analyses

Sensitivity analyses conducted as part of this study are presented in the Appendix. Firstly, given distributional concerns raised when modelling health

expenditures it was prudent to test RE models using alternative functional forms. In this context, a two-part model (probit; OLS) and a GLM (link-log; family-Gaussian) were also estimated and results are presented in Table A2.

In addition, to simulate the impact of alternative outlier pools, Table A3 reports evaluation metrics for expenditure truncated at €10,000 and €50,000, respectively.

IV RESULTS

4.1 Descriptive Statistics

Descriptive statistics are presented in Table 2. Over half of the concurrently (prospectively) insured were female. A total of 77 per cent (77.6 per cent) of insurees were aged less than 60, while 96.1 per cent (96.4 per cent) had advanced-level cover. In addition, 75.9 per cent (75.5 per cent) of the concurrently (prospectively) insured made no claim. Average claims expenditure for the concurrently (prospectively) insured was €819.65 (€834.40). The most common classifiable diagnosis was "Malignant Cancer, Leukaemia" accounting for 11.2 per cent (9.9 per cent) of concurrent (prospective) diagnoses.

4.2 Individual Prediction Metrics

Individual prediction metrics are presented in Table 3. In terms of the concurrent analysis, the demographic model performed worse (R^2 = 3.0 per cent). Model 2, with the addition of inpatient hospital nights, performed significantly better (R^2 = 45.2 per cent), while including daycase admissions (Model 3) further increased predictive ability (R^2 = 50.9 per cent). Substituting a chronic illness indicator for the daycase admissions flag (Model 4) lowered the R^2 slightly (R^2 = 47.4 per cent). Model 5 (based on ICD-9-CM groupings) explained 36.8 per cent of expenditure variation.

The demographic model had the highest (lowest) MAPE (CPM) of €1,275.42 (5.3 per cent). Model 2 performed noticeably better with a MAPE (CPM) of €871.20 (35.4 per cent). As with the R^2 metric, based on MAPE and CPM Model 3 (MAPE = €722.96; CPM = 46.4 per cent) was the best performing model.

In terms of the prospective analysis, the demographic model again predicted the least variation in claims expenditure (R^2 = 3.0 per cent). Models 2, 3, 4, and 5 all represented successive marginal improvements in R^2 (5.8 per cent, 6.8 per cent, 7.0 per cent and 16.6 per cent, respectively). MAPE and CPM provided the same model rankings as given by R^2.

Sensitivity analyses of functional form (Table A2) showed that both the two-part model and the GLM provided similar interpretations to the OLS results presented above. In terms of prediction, the two-part model performed similarly well to the straightforward OLS model, while the GLM specification performed slightly worse.

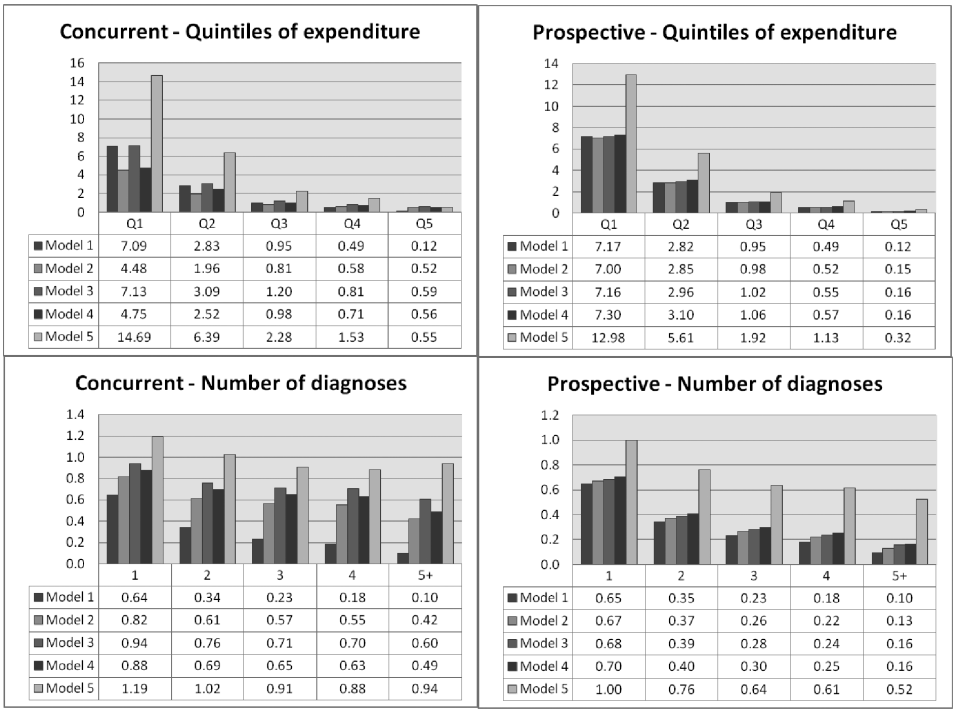
Table 2: Descriptive Statistics for Concurrent and Prospectively Insured

		Concurrently Insured % (N=1,235,922)	*Prospectively Insured % (N= 1,166,425)*
Gender	Male	47.9	47.8
	Female	52.1	52.2
Age	0-59	77	77.6
	60-64	6.3	6.4
	65-69	5.7	5.5
	70-74	4.3	4.2
	75-79	3.3	3.1
	80-84	2.1	1.9
	85+	1.4	1.2
Level of cover	Advanced	96.1	96.4
	Non-Advanced	3.9	3.6
Number of admissions	0	75.9	75.2
	1	14.6	15
	2	5.1	5.3
	3	+ 4.4	4.6
Positive claims expenditure 2012	No	75.9	75.5
	Yes	24.1	24.5
Average Claims Expenditure (S.D) 2012		€819.65 (€4,326.81)	€834.40 (€4,357.09)
		Diagnoses concurrently insured % (N= 555,205)	*Diagnoses prospectively insured % (N=549,695)*
5 most frequently recorded principal ICD-9-CM Categories	All other diagnoses	81.6	82.6
	Malignant Cancer, Leukaemia	11.2	9.9
	Maternity	1.8	2.1
	Coronary Artery Disease	1.6	1.6
	Musculoskeletal / Connective Tissue Disorder	0.7	0.7

4.3 Predictive Ratios

Predictive ratios are displayed in Figure 2. For all concurrent models, predictive ratios fell as we moved from the lowest quintile (Q1) of expenditure to the highest (Q5). All models over-predicted expenditure for Q1 and Q2 and under-predicted expenditure for Q5. As expected, Model 1 performed worst in terms of group-level

Figure 2: Predictive Ratios Broken Down by Actual (Non-Truncated) Claims Expenditure Quintiles (Q1-Q5) and Number of Diagnoses (1-5+) for Concurrent and Prospective Models



Concurrent - Quintiles of expenditure	Q1	Q2	Q3	Q4	Q5
Model 1	7.09	2.83	0.95	0.49	0.12
Model 2	4.48	1.96	0.81	0.58	0.52
Model 3	7.13	3.09	1.20	0.81	0.59
Model 4	4.75	2.52	0.98	0.71	0.56
Model 5	14.69	6.39	2.28	1.53	0.55

Prospective - Quintiles of expenditure	Q1	Q2	Q3	Q4	Q5
Model 1	7.17	2.82	0.95	0.49	0.12
Model 2	7.00	2.85	0.98	0.52	0.15
Model 3	7.16	2.96	1.02	0.55	0.16
Model 4	7.30	3.10	1.06	0.57	0.16
Model 5	12.98	5.61	1.92	1.13	0.32

Concurrent - Number of diagnoses	1	2	3	4	5+
Model 1	0.64	0.34	0.23	0.18	0.10
Model 2	0.82	0.61	0.57	0.55	0.42
Model 3	0.94	0.76	0.71	0.70	0.60
Model 4	0.88	0.69	0.65	0.63	0.49
Model 5	1.19	1.02	0.91	0.88	0.94

Prospective - Number of diagnoses	1	2	3	4	5+
Model 1	0.65	0.35	0.23	0.18	0.10
Model 2	0.67	0.37	0.26	0.22	0.13
Model 3	0.68	0.39	0.28	0.24	0.16
Model 4	0.70	0.40	0.30	0.25	0.16
Model 5	1.00	0.76	0.64	0.61	0.52

prediction for Q5 (PR = 0.12) while Model 3 performed best (PR = 0.59). Relative to the other models, Model 5 noticeably over-predicts expenditure for those in Q1 and Q2 (Figure 2). In terms of morbidity status (i.e. number of diagnoses), in general the group predictive ability of models falls as morbidity status worsens. The demographic model performs worst, with lower predictive ratios across all categories, relative to the other models. As morbidity status worsens, Model 5 becomes increasingly the best predictor of expenditure. For those with five or more diagnoses, Model 5 has a PR of 0.94.

Similar to the concurrent analysis, all prospective models over-predicted expenditure for Q1 and Q2 (particularly Model 5) and under-predicted expenditure for Q5. Under-prediction for Q5 was worse for all models (except Model 1 with the same PR) compared with the concurrent analysis. For Q5, Model 1 under-predicted spending more than all other models (PR = 0.12), while Model 5 under-predicted spending the least (PR = 0.32). As morbidity status worsens, all models increasingly under-predicted expenditure. Within all categories of morbidity, Model 5 was by far the best predictor of observed expenditure (PR = 0.52).

4.4 Expenditure Truncation

Overall, truncation had the effect of improving model fit in the prospective analysis. Results were more ambiguous for the concurrent analysis with only Model 1 and Model 5 reporting higher R^2 and CPM with truncated expenditure. All truncated concurrent models, apart from Model 3 reported lower MAPE (see Table 3).

Similar trends were observed truncating expenditure at €10,000 and €50,000 (Table A3). For the prospective analysis, truncating at €10,000 provided an unambiguously better fit than truncating at €25,000, which in turn provided better fit than truncating at €50,000.

Table 3: Individual Prediction Metrics for Concurrent and Prospective Models (Raw and Truncated Expenditure)

	*Adj. R^2 *100*	*MAPE €*	*CPM *100*
Concurrent Model – Raw Expenditure			
Demographic model (Model 1)	3.0	1,275.42	5.3
Model 1 incl. inpatient nights (Model 2)	45.2	871.2	35.4
Model 2 incl. daycase admissions (Model 3)	50.9	722.96	46.4
Model 2 incl. a chronic illness flag (Model 4)	47.4	828.28	38.6
Demographic model incl. 35 ICD-9-CM diagnosis groupings (Model 5)	36.8	744.05	44.6
Prospective – Raw Expenditure			
Demographic model (Model 1)	3.0	1,280.17	5.2
Model 1 incl. inpatient nights (Model 2)	5.8	1,250.21	7.3
Model 2 incl. daycase admissions (Model 3, current RE design)	6.8	1,231.91	8.5
Model 2 incl. a chronic illness flag (Model 4)	7.0	1,229.15	8.7
Demographic model incl. 35 ICD-9-CM diagnosis groupings (Model 5)	16.6	989.69	25.7
Concurrent – Truncated Expenditure (€25,000)			
Demographic model (Model 1)	5.1	1,080.57	5.7
Model 1 incl. inpatient nights (Model 2)	38.2	842.26	26.5
Model 2 incl. daycase admissions (Model 3)	44.3	745.9	34.8
Model 2 incl. a chronic illness flag (Model 4)	42.7	793.99	30.6
Demographic model incl. 35 ICD-9-CM diagnosis groupings (Model 5)	44.6	607.28	46.7
Prospective – Truncated Expenditure (€25,000)			
Demographic model (Model 1)	5.0	1,086.97	5.5
Model 1 incl. inpatient nights (Model 2)	7.5	1,066.98	7.2
Model 2 incl. daycase admissions (Model 3)	8.51	1,054.25	8.2
Model 2 incl. a chronic illness flag (Model 4)	9.27	1,048.17	8.7
Demographic model incl. 35 ICD-9-CM diagnosis groupings (Model 5)	23.41	814.08	28.1

V DISCUSSION

This paper focused on empirically evaluating the recent introduction of RE payments in the Irish private health insurance market. The Irish market is underpinned by the idea of intergenerational solidarity, manifested through heavy regulation, particularly community rating. However, the evolution of the market in the absence of risk-adjusted subsidies created strong incentives for risk selection and contributed to market segmentation. In the absence of subsidies, the incumbent VHI found it increasingly difficult to compete on price, undermining explicit policy objectives to provide affordable cover for high-risks. In this context, the results of this study raise a number of important, and timely, considerations.

First, concurrent models outperform prospective models. Particularly, utilisation-based models (i.e. Model 2 and 3) appear to perform comparatively well in a concurrent context and this could be related to the fact insurers pay set per diem rates for private care in public hospitals (Citizens Information 2014). Figures suggest that for those with private health insurance, just over 60 per cent of their inpatient stays take place in public hospitals (CSO, 2011).

The fact that concurrent models perform better is not a surprising result (van de Ven and Ellis, 2000; Behrend *et al.*, 2007; Chang and Weiner, 2010), however, this form of reimbursement may not be preferable in practice. Particularly, reimbursing insurers ex-post on actual expenditures recorded suggests better ability to reduce risk selection incentives as predicted costs better reflect actual costs, thus reducing insurer financial liability to a greater extent. However, this also reduces insurer incentives to behave efficiently. Moreover, retrospective payments can create uncertainties around payment allocations leading to difficulties for insurers in calculating premiums. This is a particular problem in voluntary markets where consumers use premium signals not only as a basis for insurer choice, but also in deciding whether to take out insurance at all (Armstrong *et al.*, 2010). Prospective payments may be less accurate; however, they better preserve incentives for efficient behaviour and allow insurers to ex-ante factor in the impact of credits in determining plan premiums.

Second, given RE credits in the Irish VPHI are prospectively set, a worrying finding is that the former (5.8 per cent) and current (6.8 per cent) RE designs are poor predictors of claims expenditure. As discussed earlier, RE need not be perfect, however, it should be the case that RE adequately reimburses insurers for the risk they hold to the point that the cost of investing in risk selection (e.g. marketing, product design, reputational damage) outweighs any benefits (in terms of predicable profits) (van de Ven, 2011). This study would therefore suggest that the current RE specification is unlikely to be effective at combating risk selection incentives and/or correcting for market segmentation. This is reflected in concerns raised by the HIA in 2015 that "in the last year insurers have continued to adopt strategies to segment

and select business with lower claims costs", despite the introduction of RE (HIA, 2015c). In this context, more sophisticated RE designs in Germany and Netherlands have been shown to prospectively predict upwards of 20 per cent of claims expenditure (van Veen *et al.*, 2015; Buchner *et al.*, 2013). The CMS-HCC model used by Medicare to risk-adjust capitation payments to private plans has been shown to predict approximately 12.5 per cent of claims expenditure (Pope *et al.*, 2011). Caution does need to be exercised, however, when comparing performance of RE models across systems given differences in insured populations and level of benefits covered.

Underlying these models, however, is that subsidies include payments predicated on diagnostic information. For instance, in addition to socio-economic adjusters, the 2012 Dutch RE scheme included 13 inpatient Diagnostic Cost Groups (DCGs) and 25 Pharmacy Cost Groups (PCGs) plus an adjuster for multiple-year high costs. Similarly, the German RE system and the CMS-HCC model use diagnostic information in the form of Hierarchical Condition Categories (HCC) as their basis for reimbursement. And in the context of this study, evidence would suggest that the current Irish RE design could be substantially improved through the substitution of the current utilisation-based health status adjusters for diagnosis-based high cost categories, both overall (Model 5; R^2= 16.6 per cent), and for high-risk individuals (Figure 2).[8] Another benefit of introducing a diagnostic adjuster would be that, to the extent that insurers can influence utilisation of acute services, incentives for efficient behaviour would be improved as reimbursement would not be tied directly to frequency of utilisation (e.g. number of nights spent in acute care).

An alternative, or complementary, proposal could be the introduction of an outlier-risk pool, common to many RE designs (Breyer *et al.*, 2012), whereby high-cost individuals are reimbursed ex-post above a certain threshold. However, again policymakers would need to weigh up the risk selection/efficiency trade-off of such a move.

Third, although the introduction of diagnosis-based payments in the Irish market may be beneficial, it may not be straightforward. In this regard, diagnosis-based payments were previously considered in the design of the current RE scheme[9] but were eventually rejected in favour of a hospital utilisation adjuster (HIA, 2010a). This was justified on grounds of both lack of support for diagnosis-based payments and practical difficulties with its implementation (HIA, 2010b). Recently, the implementation of diagnosis-based RE in the Irish system has been mooted again (DOH, 2014b), however, it is unclear if it is any more realisable.

[8] One caveat however, is that this model did also significantly over-predict for those in the lower quintiles of expenditure, relative to other models, which itself might distort incentives.

[9] Mention was given to both specific medical diagnoses and diagnosis-related groups (DRGs).

For instance, any form of diagnosis-based payments introduced in the Irish system would have to be acceptable to all stakeholders. In this context, RE in the Irish system, as noted, has historically been a contentious issue with concerns over its legitimacy subject to a successful legal challenge by the first market competitor. However more recently, during the consultation phase, newer entrants expressed serious concerns over the need for a health status adjuster in the current RE specification (Aviva, 2010; Quinn Healthcare, 2010). And given the asymmetry of risk in the market, VHI is a net beneficiary of payment flows while the newer entrants are net contributors (HIA, 2014c). As such, there may be significant opposition from the newer entrants to the introduction of diagnosis-based payments if such refinements reinforce the transfer of resources to the VHI.

Feasibility is another issue to consider (van de Ven and Ellis, 2000). For instance, the introduction of diagnosis-based RE would likely place a much greater administrative burden on both insurers and the regulator. It is unclear at present the extent to which all insurers have the ability to accurately capture and code relevant diagnostic information. Moreover diagnosis-based payments would increase the informational requirements of both insurers and regulators in terms of submitting and auditing, respectively, RE returns. Finally, linking payments to diagnoses may create issues in terms of insurer incentives for accurate reporting. Processes would need to be put in place to monitor and manage such activity.

Fourth, a separate issue is the impact that recently introduced lifetime community rating may have on the market. For instance, as a form of risk-rating, lifetime community rating may complement RE subsidies in reducing selection incentives. However, if lifetime community rating encourages younger cohorts to take out insurance (as it is designed to) and if, for instance, newer entrants are better able to capture these risks this could contribute to further market segmentation. Low-risk consumers, in this context, might be attracted to low-cost policies (as a cheap way of avoiding loadings), something the newer insurers, given their already better risk profiles (due to lack of robust RE) may be better able to provide.

Finally, results from this analysis add to current evidence that cautions against expanding the role competitive health insurance plays in the Irish market. While previous analyses have suggested universal health insurance to be undesirable from a cost perspective, this study suggests that competitive foundations for such a model, in the form of a robust RE, are currently not in place. Aside from the importance of RE in a voluntary market, it is considered a crucial precondition for effective managed competition (Bevan and van de Ven, 2010).

5.1 Limitations

Regrettably, due to data limitations, more established diagnosis-groupers such as CMS-HCC or DCG/HCC models (Duncan, 2011) could not be tested. However, results would suggest that future research into the application of other forms of

diagnosis-based payments in the Irish system would be worthwhile. Another limitation of this study is that analysis is predicated on data from one (albeit the largest) insurer in the market with a worse than average risk profile. This may have some implications for generalisability of findings.

VI CONCLUSIONS

This study empirically analysed the efficacy of the recently introduced RE scheme in the Irish VPHI market and whether improvements could be made to its specification. Importantly, this study suggests that in a prospective context, the current RE design performs poorly and may not be addressing risk selection incentives, nor correcting for acute risk segmentation, that have historically characterised the market. In this context, evidence suggests that the RE design could be substantially improved through the substitution of the current hospital utilisation risk adjusters with one based on high-cost diagnosis groups. However, policymakers should be cognisant of issues around feasibility and acceptability related to the introduction of diagnosis-based payments in the Irish market. This study is particularly timely given recent health system proposals discussing transition from a voluntary to mandatory health insurance system.

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APPENDIX

Table A1: ICD-9-CM Diagnostic Categories

CD-9-CM Diagnostic Category	
1 Alcoholism	19 Haemophilia
2 Chronic Kidney Disease	20 Hyperlipidemia
3 Chronic Pulmonary Disease	21 Hypertension
4 CNS (MS)	22 Infectious Disease (Hep A-E, HIV)
5 CNS Disorder (Cerebral Palsy)	23 Infectious Liver Disease
6 CNS Disorder (Parkinson)	24 Malignant Cancer, Leukaemia
7 CNS Disorders	25 Maternity
8 Congestive Heart Failure	26 Mental disorder
9 Coronary Artery Disease	27 Mental disorder (Schizophrenia)
10 CVA Stroke	28 Metabolism Disorders (Cystic Fibrosis)
11 Dementia	29 Musculoskeletal/ connective tissue disorder
12 Depression	30 Polycystic Ovary Syndrome
13 Diabetes	31 Peripheral Vascular Disease
14 Disorder of the adrenal glands	32 Renal Failure
15 Drug Abuse	33 Severe Chronic Liver Disease
16 Epilepsy	34 Systemic Lupus Erythematosus
17 Gastrointestinal Disease (Crohns)	35 All other diagnoses
18 Gastrointestinal Disease (Ulcerative Colitis)	

Note: Full list of individual principal ICD-9-CM codes used for categorisations available on request.

Table A2: TPM and GLM specifications

Concurrent							
	TPM (First-part: Probit, Second-part: Linear)				*GLM (Link:Log, Distribution:Gaussian)*		
	*Adj. Pseudo R^2*100*	*MAPE*	*CPM *100*		*Adj. Pseudo R^2*100*	*MAPE*	*CPM *100*
Model 1	3.0	1286.17	5.3	Model 1	3.0	1286.17	5.3
Model 2	49.4	767	43.5	Model 2	31.5	1056.8	22.2
Model 3	52.9	587.26	56.8	Model 3	23.9	907.08	33.5
Model 4	50.1	747.21	45.1	Model 4	31.1	1015.56	25.3
Model 5	37.6	695.96	48.8	Model 5	20.2	865.23	40.0
Prospective							
	TPM (First-part: Probit, Second-part: Linear)				*GLM (Link:Log, Distribution: Gaussian)*		
	*Adj. Pseudo R^2*100*	*MAPE*	*CPM *100*		*Adj. Pseudo R^2*100*	*MAPE*	*CPM *100*
Model 1	3.0	1290.64	5.2	Model 1	2.9	1290.64	5.2
Model 2	5.0	1262.56	7.2	Model 2	4.3	1291.91	5.1
Model 3	5.9	1242.48	8.6	Model 3	5.0	1284.05	5.7
Model 4	6.4	1242.73	8.6	Model 4	5.6	1276.71	6.2
Model 5	17.4	954.3	29.5	Model 5	10.2	1176.17	26.2

Table A3: Individual Prediction Metrics for Concurrent and Prospective Models, Truncated at €10,000 and €50,000, Respectively

	*Adj. R^2 *100*	*MAPE €*	*CPM *100*
Concurrent –Truncated €10,000			
Model 1	6.1	842.79	5.9
Model 2	28.5	720.06	19.6
Model 3	34.3	662.23	26.1
Model 4	34.3	676.33	24.5
Model 5	49.5	449.97	49.8
Prospective – Truncated €10, 000			
Model 1	6	856.84	5.7
Model 2	7.9	845.03	7
Model 3	8.8	837.21	7.9
Model 4	9.9	830.14	8.7
Model 5	28	644.19	29.1
Concurrent – Truncated €50,000			
Model 1	4	1,217.08	5.5
Model 2	43.5	883.44	31.4
Model 3	49.8	757.34	41.2
Model 4	46.8	836.88	35
Model 5	43.5	703.27	45.4
Prospective – Truncated €50,000			
Model 1	3.9	1,243.03	5.3
Model 2	6.8	1,217.92	7.2
Model 3	7.9	1,202.56	8.4
Model 4	8.4	1,198.69	8.7
Model 5	20.4	964.24	26.5