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Risk Adjustment

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Abstract

Risk adjustment is used to make payments or allow comparisons of outcomes while controlling for exogenous risk factors that explain variations in the outcome of interest, such as spending, utilization, quality, or death. This article focuses on conceptual and empirical uses of risk adjustment in health economics, where patient-level risk factors are commonly used to explain spending and other outcomes.

Keywords

Health Economics, Health insurance, Medicare, Medicaid, adverse selection, biased selection, health plan choice, life insurance,…

Article

Risk Adjustment

is a term used in health economics to describe the use of exogenous risk factors to explain variations in health care spending, utilization, quality or outcomes of interest, such as death or health status (van de Ven and Ellis, 2000; Ellis 2008). It is also used more broadly by actuaries and others when predicting any outcome that varies systematically with covariates. For example, actuaries perform risk adjustment when setting premiums for life insurance to reflect age and gender (Gründl, Post, and Schulze, 2006), or when setting premiums for property insurance related to geography or rate classes; risk adjustment terminology is also used in the finance literature (e.g., Constantinides, 1978). Use of “risk adjustment” for health care markets is the focus of the remainder of this article.

The American Academy of Actuaries (2010) defines risk adjustment as "an actuarial tool used to calibrate payments to health plans or other stakeholders based on the relative health of the at-risk populations." Risk adjusting payments to health plans by a payer is an important tool for reducing incentives for health plans to adopt strategies that induce favorable selections, and avoid market failures due to adverse selection. Risk adjustment is widely used in publicly funded insurance programs, including US Medicare and Medicaid managed care programs, and the competitive insurance markets in Belgium, Germany, Israel, Netherlands, and Switzerland. Risk-adjusted payments play a key role in many proposals to broaden access to insurance and promote incentives for low cost effective health care, including the health insurance exchanges proposed as part of the Patient Protection and Accountable Care Act (PPACA) of 2010.

Risk adjustment is also commonly used in program evaluation where the interest is in normalizing populations with different underlying risks so as to compare outcomes. This use is also often called "case-mix" or "severity" adjustment, particularly when used to explain variation in outcomes for a particular procedure or episode of treatment, notably including the literature on Diagnosis Related Groups (DRGs) as introduced by Fetter, Shin, Freeman et al (1980). It would promote clarity among economists to distinguish risk adjustment from case-mix adjustment, although the classic book on risk adjustment edited by physician Lisa Iezzoni (2003, 3rd edition) uses risk adjustment to refer to all kinds of risk, case-mix and severity adjustment. A rich literature focuses on the actuarial use of risk adjustment for entire groups of enrollees (see especially Rice and Smith, 2001 and Duncan, 2010)), but increasingly, as data improve, risk adjusting with individual rather than group level data has become the norm. In recent years the terminology "predictive modeling" has come to be used in the US for models designed for predicting individual-level health care utilization without regard to whether the predictive model will be used for payment. Such models can be useful when payment (and hence incentives) are not of concern, for example, for prospectively identifying high cost cases to manage.

Theory of Risk Adjustment

Early work in developing risk adjustment models focused on the statistical problem of maximizing the amount of variance in total spending that can be explained with available information (Ash et al, 1989). Even in this early work it was recognized that if lagged utilization or spending variables are used as explanatory variables, then the model is not only capturing underlying illness burden, but also consumer taste for treatment and provider practice variation, which one is often trying not to do for incentive reasons. Early work focused on measures plausibly capturing health status, including self-reported health

and chronic condition measures, as well as claims-based diagnoses. More recently pharmacy-based information has been used to predict spending, and in the Netherlands now serves as a central part of its risk-adjusted equalization of funds across competing health plans (van de Ven et al, 2004). The consensus view among risk adjusters and policy makers is that diagnoses and pharmacy signals, while not fully exogenous, are less endogenous than many other variables (such as health plan, provider type, access, taste, and consumer lifestyle), and hence these variables are the most widely used for risk adjustment. From the onset, it has been recognized that health status information (whether self-reported, diagnoses or pharmacy) can either be used to predict outcomes from the same period or the period subsequent to being observed. The former is called concurrent (or sometimes retrospective) risk adjustment, while the latter is prospective risk adjustment. Most payment systems use prospective risk adjustment, due to both concerns about endogeneity of the signals, as well as practical reason that it means that risk factors can be measured, in principle a year earlier than the spending being predicted. Concurrent models always have higher explanatory power than prospective models. For quality measurement or normalization of many performance measures, a concurrent framework is also used.

An early contribution to the risk adjustment literature was by Newhouse et al. (1989) who used fixed effects in panel data to calculate that a "lower bound on the upper bound" of what is potentially explainable at the individual level using time-invariant, prospective information. They show that only on the order of 20 to 25 percent of total health care spending variation is explainable, that is, no model using lagged information should be expected to achieve a higher R^2 when predicting total spending. The potentially achievable R^2 varies with the population, year, and data quality, but the upper bound remains on the order of 30% in more recent data. This limit is humbling, until one realizes that predictability over a one-year period at the individual level in many other insurance settings (e.g., fire, life, property) is even less.

Glazer and McGuire, (2000 and 2002) were the first to develop theoretical models characterizing "optimal risk adjustment," which they distinguish from the existing statistical models that do "conventional risk adjustment." Alternative models of optimal risk adjustment are further developed in Shen and Ellis (2002) and Jack (2006). Whereas a hallmark of conventional risk adjustment is the goal of unbiasedness - paying each plan or normalizing utilization measures so that predicted levels equal actual levels - the essence of optimal risk adjustment is to examine biased risk adjustment models which optimally correct for incentive problems in health care markets. Glazer and McGuire (2000) model the selection problem as one in which competing health plans oversupply services that attract the healthy (e.g., acute care), and undersupply services that disproportionately attract the high cost, relatively sick

(e.g., chronic care services). Since the signals used for risk adjustment are never perfect, by distorting services in this way, even with conventional risk adjustment paying the expected costs, it will be optimal for health plans to distort services offerings so as to attract the relatively healthy within a payment category, and deter the relatively sick. Ellis and McGuire (2007) document that there is evidence that Medicare health plans have incentives to distort services precisely in this way, even with a rich conventional risk adjustment. The solution Glazer and McGuire devise is to overpay on signals predicting a greater likelihood of being high cost, and underpay on signals predicting low cost, so as to undo the incentive to undertreat the high cost enrollees. For example if only half of patients with asthma in a plan have their diagnoses recorded in the base period, and the incremental cost of the observed asthma patients is $500 higher than expected, then the plan should be paid twice this increment, or $1000 to compensate the plan for the under-reported patients with asthma. Conversely, one should pay less than the observed average cost for healthy signals in order to keep overall payments neutral. This twist in payments can in theory undo incentives to undertreat in capitated payment systems.

There are several challenges to implementing Glazer and McGuire's optimal risk adjustment formulas. These include the substantial information needed to assess levels of under- and over reporting of each signal used for risk adjustment; understanding the reaction function of providers to alternative marginal risk adjustment payment rates; and ensuring that all relevant provider behavior is captured by the model. Glazer and McGuire model the problem as one of service distortion to attract a favorable selection, while policy makers have typically been more concerned about increased incentives to upcode patient severity by recording more diagnoses once risk adjustment is implemented. While optimal risk adjustment is an important conceptual framework , it has so far proven challenging to implement in practice.

Information used for Risk adjustment

Ellis (2008) reviews the different types of information that can be used to predict health care spending. Variation in spending can be decomposed conceptually and empirically into variation due to patient characteristics, characteristics of the providers they see (e.g. specialists, general practitioners, hospitals, nurses), and the prices of the services actually provided. Depending on the purpose, all of this information may be useful for prediction, but it is not necessarily exogenous, and good instruments to control for endogeneity are often scarce. Patient characteristics can be further decomposed into variations due to the underlying health status of the patient, socioeconomic variables such as income and education; enabling information such as benefit design and geographic location that affect access and utilization, and patient tastes. The best set of information to use for risk adjustment depends upon the intended use.

Health-based payment models and severity adjustment models restrict the information set to only use health status. Needs-adjusted payment, widely used in Europe, broadens the information to reflect further demographic variables such as income, race, geography, and access (e.g., distance). Van de Ven et al. (2003) provides a useful overview of how risk adjustment is being done in five European countries with multiple, competing health plans.

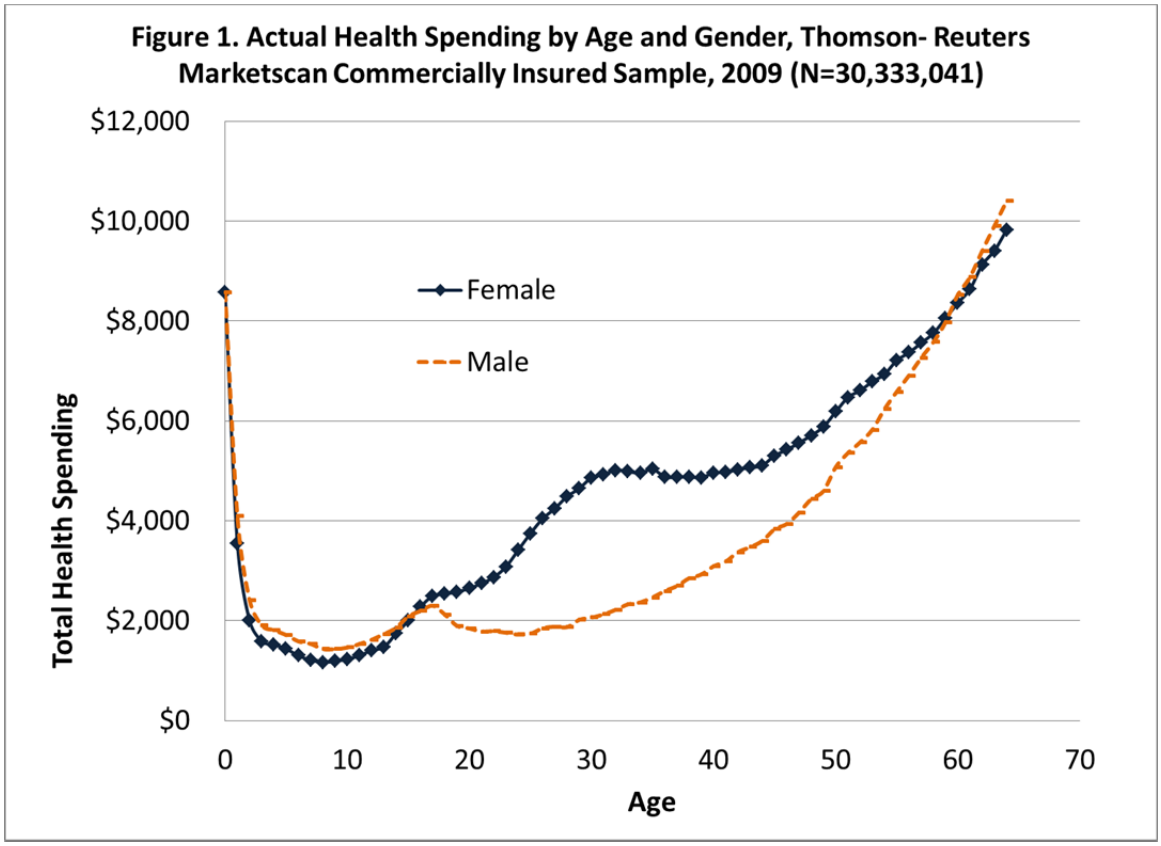
For the US Medicare Advantage (Part C) program, which is offered as a voluntary alternative to the conventional Medicare to all enrollees, risk adjusted payments to health plans from 1985 to 1999 used only age, gender, Medicaid eligibility, institutional status (i.e., whether in a nursing home) and the county of residence of the enrollee. Since 2000 risk adjustment in the US Medicare program has used diagnostic information, initially using only inpatient diagnoses but since 2004 diagnoses from outpatient clinician claims have also been used (CMS, 2006). After considering numerous alternative classification systems for diagnostic information, the Medicare program chose to implement the CMS Hierarchical Condition Category (CMS-HCC) classification system using 70 diagnostic groups for prediction (Ash et al, 2000, Pope et al, 2004). As of 2011, up to 86 HCCs are used, and the system is also used for Medicare Part D which includes prescription drug plans (Robst et al, 2007).

In the United Kingdom (UK), risk adjustment has been used for many years to allocate funds between geographically defined "Primary Care Trusts" using a variety of need, and done at the group level. Rice and Smith (2001) provide an overview of this approach. More recent efforts in the UK have considered using individual information for risk adjusting payments not only to the geographically defined PCTs, but also to individual general practitioners (Dixon et al., 2011). The main drawback to using individual-level diagnostic information has been to obtain this information from office based physicians, who are not required to record diagnoses as a condition of service payments. Dixon et al demonstrate that models using only inpatient diagnoses, and counts of office visits and facility visits, have impressively high explanatory power, as discussed further below.

Empirical Risk Adjustment Models

The classic approach to risk adjustment is to use only truly exogenous information, such as age and gender. Figure 1 illustrates the importance of using relatively flexible specifications for even capturing age and sex adjustment of total health spending. The figure highlights that babies are disproportionately expensive, women cost more than men through their childbearing years, while in childhood males are slightly more expensive. These patterns are poorly captured by including a linear age term, even when using third or fourth degree polynomials of age. Most sophisticated risk adjustment models calibrated on

large samples use 30 or more age-sex dummy variables to capture this nonlinear pattern (Ash et al, 1989; Pope et al 2004; Dixon et al, 2011).



Notes: Sample used is the US 2009 Thomson-Reuters MarketScan Commercially Insured Claims and Encounter Data. All plan types and individual with a valid sex and age <65 were included, although persons without pharmacy coverage were excluded. Each point plotted is the one year average total covered health spending per capita (medical plus pharmacy spending, including deductibles and copayments, but excluding dental and vision spending) for that one year age and gender group. (Source: Author's original figure.)

Rather than only using exogenous age and gender, the most common approach used for risk adjustment is to use the rich information appearing on insurance claims as a proxy for individual health status. The most widespread information used is diagnoses, although pharmacy information is also common. Utilization measures (e.g., spending, hospitalizations, and counts of visits) are also highly predictive of future spending, although contribute relatively modestly to the predictive power once a rich diagnostic model is used. Although claims-based information is only recorded when a visit to a health care provider is made, and is potentially "gameable" or amenable to manipulation, their strong predictive power and availability make them highly attractive. There are a number of careful reviews of alternative risk

adjustment models. These include US classics by Ingber (1998) and Pope et al (1998), the Society of Actuaries (Winkelman and Mehmud, 2007), provider profiling models by Thomas et al (2004), and comparisons done in Canada (Berlinguet, 2005), Germany (Wasem et al, 2006) and the impressively comprehensive study of multiple classification systems and information datasets done in the UK by Dixon et al (2011).

A review of the many systems available for classifying diagnoses and pharmacy information would take much longer than the space of this definition. A glimpse at the dimensions along which five of the major diagnosis based models vary is summarized in Table 1, compiled by the State of Florida Medicaid program when comparing alternative diagnosis based models.

Table 1 Risk Adjustment Model Comparison, State of Florida Medicaid Program.

Risk-Adjustment Model Comparison

May 7, 2009

Model Feature	Adjusted Clinical Groups (ACGs)	Chronic-Illness Disability Payment System (CDPS)	Clinical Risk Groups (CRGs)	Diagnostic Risk Group (DCG)	Episode Risk Groups (ERGs)
Background					
Model Developer	Johns Hopkins	University of California, San Diego (UCSD)	3M Health Information Systems	Verisk Health (formerly DxCG)	Ingenix (formerly Symmetry)
Marketplace Introduction	1992	1996	2000	1996	2001
Disease Classification					
Additive/Categorical Classification	Categorical	Additive	Categorical	Additive	Additive
Diagnoses (Dx)	Single diagnosis	Single diagnosis	Single diagnosis from inpatient facility or two diagnoses from professionals	Single diagnosis	Single diagnosis from face-to-face encounter or inpatient admissions
Conditions Included	Acute and chronic	Chronic only	Acute and chronic	Acute and chronic	Acute and chronic
Model Users					
Government Programs to Adjust Capitation Payments	4 Medicaid	10 Medicaid	1 Medicaid	Medicare	1 Medicaid
Commercial	175	None	7	300+	60
Estimation Capabilities[1] (Prospective R-Squared)					
Without Truncation	16.6%	14.7%	N/A[2]	17.8%	16.4%
Truncated at $100,000	21.8%	20.8%	N/A	24.9%	24.4%

Notes: For further details of each of the systems listed, see Weiner, et al., 1991; Kronick and Dreyfus, 1996; Averill et al, 1999; Ash, et al., 2000; and Symmetry Health Data Systems, Inc., 2001.

Source for this table:
http://ahca.myflorida.com/Medicaid/quality_management/workgroups/managed_care/5_rar_model_comparison_050709.pdf

Table 2 illustrates several important findings from Dixon et al. (2011) using UK data that have also been shown in other countries. Looking first across the rows, age and gender alone only explain about 3-5 percent of total variation at the individual level. Also striking is that once diagnostic and utilization information are included in model (b) surprisingly little further variation is explained by including geographic variation (as captured by 152 primary care trust dummies, which are geographical), 135 need variables (e.g., income, education, and prevalence of selected chronic conditions in the area) and 63 supply side variables (e.g., numbers of providers of various types and distances). Explanatory power at the individual level as measured by the R^2 differs only in the third or fourth decimal. The final row reveals that dropping the four utilization variables has a more significant effect on the model's predictive power, losing about half of the models explanatory power. Many would argue that the four lagged utilization variables are not only picking up health status heterogeneity, but also patient and provider taste variation. (Key need and supply side variables are still included in the model.)

Looking across the columns of Table 2 reveals that with 5 million observations in the estimation sample, there is no overfitting problem, even with over 500 right hand side explanatory variables. The final column shows that despite having only modest explanatory power at the individual level, where there is lots of individual patient randomness, the models do enormously better at the practice level where much of this randomness averages out. The third column sums up patient actual and predicted spending to the level of 797 primary care practices (averaging just over 6,500 patients per practice) before using the conventional R^2 to calculate predictive power. The explained variation in spending at the practice level (the R^2) starts at 34 percent for the age gender, and increases to just over 80% once geographic dummies are added in. Even the final model, which does not use the four utilization variables capturing patient and provider taste variation, explains 77% of practice-level variation in spending.

Table 2. Selected Results from Dixon et al (2011) Predicting FY2008 Health Spending per Capita Using Prior Two Years of UK Data

ID	Explanatory variables in OLS models:	Number of parameters	Individual level R^2		Practice level R^2
			Estimation Sample N=5,206,651	Validation Sample #1 N=5,205,747	Validation Sample #2 N=797
a.	Age and gender only	38	0.0373	0.0366	0.3444
b.	Model (a) plus 152 diagnosis groups and 4 lagged utilization variables	194	0.2656	0.2610	0.7394
c.	Model (b) plus 151 geographic dummies	345	0.2659	0.2612	0.8046
d.	Model (c) plus 135 attributed need and 63 supply variables	543	0.2662	0.2615	0.8254
e.	Model (c) plus 7 attributed need and 3 supply variables	355	0.2671	0.2622	0.8254
f.	Age/gender, 152 diagnosis groups, 151 geographic dummies, 7 attributed need and 3 supply variables	351	0.1272	0.1229	0.7738

Notes: diagnosis groups use only inpatient diagnoses from a two year period.

Utlization variables include inpatient episode count, outpatient visit count, dummy=1 if any priority referral, and dummy=1 if any outpatient visit; all measures are for prior two years

Estimation sample is a 10% random sample of the UK population

Validation Sample #1 is a different 10% random sample of the UK population drawn without replacement

Validation Sample #2 is a 100% sample of patients at 10% of primary care practices.

See further details in Dixon et al (2011), especially Table 7.4 and Appendix 13, Table 9.

http://www.nuffieldtrust.org.uk/sites/files/nuffield/document/Developing_a_person-based_resource_allocation_formula_REPORT.pdf

Econometric Issues

Risk adjustment models have been an active area for testing and developing new estimation techniques. Early models used primarily linear models in part because the very large sample sizes and large number of explanatory variables made estimation of nonlinear models time-consuming if not infeasible (Ash et al, 1989). Since the 1990s and 2000s, there has been a surge of interest in building robust nonlinear models that are less sensitive to outliers that are common in highly skewed expenditure data. The two-part log linear model pioneered by Duan et al (1983), and used so widely in the Rand Health Insurance Experiment (Newhouse, 2002) was largely laid to rest by Manning and Mullahy (2001) who demonstrated the severe problems caused by uncorrected heterogeneity in such models. Basu et al., (2004) show the superiority of Cox Proportional Hazard models, while Buntin and Zaslavsky (2004) implemented the Generalized Linear Models (GLM), which Manning and Mullahy (2005) further refine, developing an algorithm for choosing among alternative, non-nested model specifications.

In recent years there has been a return of support for least squares models. The preferred approach adopted by the US Medicare program has consistently been since the 1980s to use weighted least squares on annualized spending, which is to say that actual spending is divided by the fraction of the year a person is eligible to annualize, and this annualized amount is weighted by the fraction of the year a person is eligible to generate unbiased means. Such an approach replicates the mean exactly in disjoint groups, and is the only demonstrated approach that easily accommodates individuals with partial year eligibility (Ellis et al, 1996). The megasamples of multiple millions of observations, as shown in Figure 1, and Table 2 in this article, largely alleviate concerns about overfitting of outliers even with great skewness.

Future Directions in Risk Adjustment

As mentioned earlier, risk adjustment figures prominently in the US PPACA of 2010, notably in the proposals for establishing insurance exchanges to serve the individual and small group insurance markets. To keep insurance affordable, premium subsidies will be offered by the government, and premium rate bands will limit premiums variations across age and gender groups to be no more than three to one. It is readily seen from Figure 1 above that in the absence of regulation, plans would choose to charge 64 year old males a premium that is nearly ten times that of an 10 year old male. Such regulated premiums can only be feasible if premium subsidies to plans are risk adjusted so that plans are paid for enrolling the aged and relatively unhealthy.

Another second important area for risk adjustment is in bundled payments to Accountable Care Organizations, which are moderate-size health care provider networks willing to receive a bundled payment in exchange for taking responsibility for providing all care to a panel of patients. Given the modest size of these panels, risk adjustment will be critical for ensuring that both healthy and sick enrollees are welcomed in the ACO.

A third important area for risk adjustment is in bundled payment for primary care, particularly as part of the Patient-Centered Medical Home. In this CMS initiative, the Medicare program is encouraging primary care providers to take responsibility for providing comprehensive primary care for patients from all payers (Medicare, Medicaid, and private) and offering increased primary care "base payments" for the extra effort this will take (beyond what they will be reimbursed for via FFS), payments that will be partial capitation amounts, not fee-based. Sizable bonus payments are also contemplated to reward primary care practices for achieving specified quality, cost and patient satisfaction targets. If either the base payments or bonus payments are not risk adjusted, then primary care practices could potentially act like insurance companies, striving to attract the healthy and avoid the relatively sick, undermining the potential of the PCMH initiative.

To date, risk adjustment models in the US have relied primarily on demographic and claims-based (usually diagnostic) information to adjust payments, utilization and outcome measures. Occasionally self-reported information is used, although the relatively high cost of surveys and consumer input limit the widespread use of such information. A potentially huge source of information for the future are electronic health records, which capture not only what treatments are done, but also the results of various biometric and laboratory tests and imaging procedures. Health records will be challenging to use, but offer rich possibilities for improved prediction of diverse outcomes of key interest to researchers and policymakers.

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