

The History and Philosophy of CBIS

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Risk at Lloyd's of London - 1688

- Insurance began at Lloyd's coffee house in 1688, which was a popular place for sailors, merchants, and ship owners, and Lloyd provided reliable shipping news.
- Syndicates made bets on safe passage.
Risk of loss was determined by:
 - condition of the ship
 - ship's route
 - type of cargo (perishable; cost)
 - weather reports
 - captain's experience and reputation
- Examples of a person's past discipline and responsibility have always been predictive of current risk of loss.



CBIS is not intuitive

Q: What is the connection between a person's credit profile and her likelihood of having an insurance loss?

A: The American Academy of Actuaries' *Risk Classification Statement of Principles* says the test of a valid risk classification characteristic is whether there is a "reasonable relationship" between the characteristic and the hazard insured against:

[I]n insurance it is often impossible to prove statistically any postulated cause and effect relationship. Causality cannot, therefore, be made a requirement for risk classification systems.



Often causality is not used in its rigorous sense of cause and effect but in a general sense, implying the existence of a plausible relationship between the characteristics of a class and the hazard insured against. Living in a river valley would not seem to cause a flood insurance claim, but it does bear a reasonable relationship to the hazard insured against and thus would be a reasonable basis for classification.

Risk classification characteristics should be neither obscure nor irrelevant to the insurance provided; but they need not always exhibit a cause and effect relationship.

Measuring risk

- How to measure serendipity?
- Law of large numbers gives macro data:
 - average = expected value over large sample
 - e.g., batting average; roulette
- Rating techniques can assign risk ranking at the individual level (e.g., Moneyball).



Rating is quantifying risk

- Each applicant presents a risk of loss. Rating is a technique to *quantify* the risk of loss.
 - The higher the risk, the higher the premium.
- Rating and underwriting depend on *risk ranking*.
- Where risk is unknown, rate builds in a *risk premium*.

Example: Basel III and Dodd-Frank require capital retention (i.e., cushion) based on the size and riskiness of a creditor's loans and investments

Risk premium

- When an insurer has more confidence in the rates, there is less need to build in a risk premium
- Better risk selection means
 - (i) an insurer is more willing to underwrite more applicants
 - (ii) with rates that are lower
- CBIS is not a redistribution of insurance premiums: it is a reduction of the risk premium



Rating factors: the science and the art

- Before statistics, rating and underwriting was done by raters' instincts and biases
- With statistics, insurance is based on a large number of similar exposure units:
“exposure units” = rating factors (the science)

“similar” = actuarial discretion (the art)



Actuaries select rating factors: the data determines the rates

- Actuaries look for *risk splitters*, which are factors that reliably (predictively) separate one risk from another
- Actuaries are *factor agnostic* (if data is reliable and easily collected)
- Models are built with depersonalized data, with no preconceptions about results.
- Models are multivariate = factors interrelate



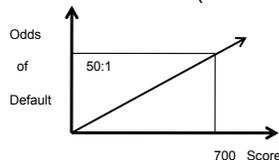
Risk splitters

- Actuaries would use any factor if:
 - a risk splitter (e.g., vehicle color);
 - easily and reliably collected; (e.g., credit profile)
 - not a proxy or double counted (e.g., income and home value)
 - not unfair (e.g., mileage), easily manipulated (e.g., favorite color), or illegal (e.g., genetics)
- Next great risk splitters?
 - usage based insurance
 - birth order



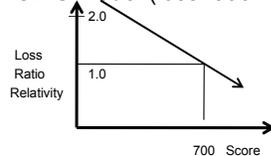
Scoring models are rating tools

- Models assign *values* to risk factors; group *similar* exposure units together – what risk is being quantified?
- FICO's multivariate algorithms produce:
Credit risk model (odds-to-score ratio)



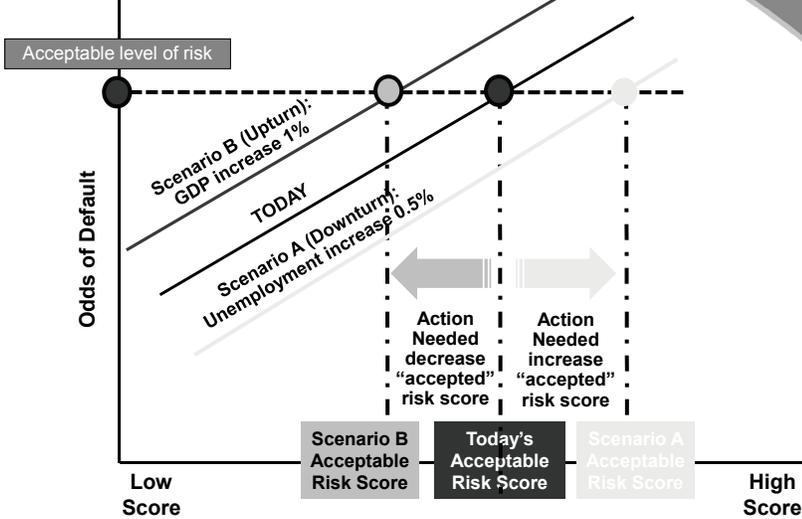
Rank order is consistent over time
Odds-to-score ratio can fluctuate
(angle of line can change)

CBIS model (loss ratio relativity-to-score ratio)



- The score (model's output) rank orders risk so that rating decisions can be made.

Impact when economy changes



FICO models predict behavior

- Other FICO models use demographic and credit data to predict events and behavior:
 - Credit Capacity Index
 - Economic Impact Index
 - Strategic Default Score
 - Medication Adherence Score
 - Usage-Based Insurance
 - Falcon Insurance Fraud Manager
- Models are built with depersonalized data



Regulators enforce rating laws

- There are social reason why certain rating factors should be disallowed in the rating process – even if predictive
- Regulators will prohibit rates if they are inadequate, excessive, or unfairly discriminatory:

Standards

inadequate

excessive

unfairly discriminatory

Regulatory Concerns

financial security of insurer

consumer protection

legal or societal



Discrimination is actuarial; unfair discrimination is illegal

- Choosing rating factors and similar exposure units involves discrimination
- There are three types of unfair discrimination:
 - based on prohibited factors (unfair or deceptive acts and practices statues and regulations)
 - based on proxy factors (e.g., wearing hijab; *Ebony/Jet* subscription)
 - disparate impact (race-neutral rating factors, where intent is not relevant)
- CBIS does not discriminate on any of these bases

FTC Report to Congress

- *Credit-Based Insurance Scores: Impacts on Consumers of Auto Insurance (Federal Trade Commission 2007):*
 - The large savings in cost and time that have accompanied the use of credit scoring are generally believed to have increased access to credit, promoted competition, and improved market efficiency. . . . The credit history scores evaluated [for the study] are predictive of credit risk for the population as a whole and for all major demographic groups. That is, over any credit score range, the higher (better) the credit score, the lower the observed incidence of default. [p. S-1]
* * *
 - The limited available evidence, including from public comments and previous research, suggests that credit scoring has increased the availability and affordability of credit . . . Credit scoring likely increases the consistency and objectivity of credit evaluation and thus may help diminish the possibility that credit decisions will be influenced by personal characteristics or other factors prohibited by law, including race or ethnicity. Credit scoring also increases the efficiency of consumer credit markets by helping creditors establish prices that are more consistent with the risks and costs inherent in extending credit. By providing a low-cost, accurate, and standardized metric of credit risk for a pool of loans, credit scoring has both broadened creditors' access to capital markets and strengthened public and private scrutiny of lending activities. [pp. S.3-S.4]