White Paper

Risk-Based Audits: Principles and Implementation

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This white paper is intended for audit managers and analysts in revenue agencies. While we mostly discuss tax administrations here, this material also applies to other revenue agencies, such as customs authorities and social security agencies.
PRINCIPLES OF RBA

The classical approach to Risk-Based Audits (RBA)

Modern data-mining techniques enable the audit analyst to assign a risk score to each taxpayer. This risk score reflects the propensity of the taxpayer to comply with existing tax provisions. It is based on: (i) the taxpayer’s attributes (size, industry, compliance history, etc.); (ii) knowledge acquired during previous audit campaigns, regardless of the selection strategy employed.

Risk scores drive the design of better audit plans, making it possible for the audit case selection process to focus on the most risky taxpayers. In addition, these scores provide tax administrations with individual risk profiles of taxpayers. These profiles not only signal those most likely to be non-compliant but also provide reasons for potential non-compliance.

This is the classical approach to RBA. It builds on decades of experience in risk scoring in the banking and insurance industry, as well as in the tax administrations of OECD countries. It follows a clear, easy to replicate logic with well-defined steps.

Beyond revenue collection enforcement, it can be applied to any set of regulations that are enforced through ex-post inspections or audits (for example social security agencies or even environmental/security/work regulations enforced by inspections).

The data requirements of RBA

Basic data

Modern risk-based audit techniques rely on the systematic use of data. But what data precisely are we talking about? The two primary sources of data are:

- Data acquired during previous inspection or audit campaigns. Audits and inspections are unique opportunities to reveal the true type and behavior of the taxpayer or company. These data are critical to characterize the profiles of non-compliant taxpayers.
- Data on individual characteristics of taxpayers. In addition to audits, administrations collect a lot of information on their taxpayers, including through periodic return filing. This body of data is called taxpayers’ ‘attributes’ in risk scoring and typically includes detailed financial data, the nature of the activity conducted, number of employees, type of ownership, etc. This body of data is available for all taxpayers or companies, not only those that were audited in the past.
The good news is that these data are routinely available on the servers of any tax administration or indeed any revenue or regulatory agency that performs audits and inspections to enforce compliance.

**Additional data**

Beyond the data directly collected by the revenue agency, additional sources of information can be tapped by the most data-savvy organizations (Vellutini 2011a). Third-party sources typically include other public-sector agencies such as other revenue agencies (e.g. customs for tax departments and vice versa) and the central bank, as well as private-sector institutions such as banks and insurance companies.

These data improve the information available on the taxpayers concerned and therefore increase the quality of any data-based audit case selection process. For example, using the compliance history from customs is typically efficient in improving audit targeting by the tax administration. Similarly, cross-checking transactions recorded by banks and insurance companies with those declared in tax returns is almost always very powerful.

Two important points should however be borne in mind:

- **Privacy laws restrict the use of individual or company information for any purpose other than that of the agency that collected the information first-hand.** For example, a tax administration is normally not allowed to use or even access micro-level data collected by the country’s statistics institute, typically through surveys. While it may be argued that this allows non-compliant individuals and firms to get through the net, the current legal arrangement in most countries is based on the notion that individuals need protection from the power of modern-day database systems.
- **Even in the realm of what is strictly legal, the technical challenges of database integration should not be underestimated.** A crucial question is how to unambiguously identify taxpayers. Many emerging countries do not have a single identification number for their taxpayers; customs have their own ID scheme, the tax administration another and social security agencies each have yet another number. Because non-compliant firms are quick at creating multiple legal shells to shelter themselves from auditing, the lack of a centralized ID for firms is a key challenge in ensuring compliance.

**Data exchange & RBA**

A question that often arises is whether efficient data exchange on undeclared activities is a substitute for risk analytics? By data exchange, we mean cross-administration and/or cross-border exchanges of information on taxpayers’ undeclared bank transactions and deposits
and other potentially illegal activities. For example, it is well known that tax authorities in OECD countries have used bank information from tax havens to launch targeted audits.

The answer is that data exchange is a (powerful) complement to analytics, but not a substitute. More and better data on taxpayer behavior means better risk modelling; identifying taxpayers with the highest compliance risks will work better still.

**Supervised vs unsupervised learning**

Data mining techniques for fraud prevention broadly fall into two categories: supervised and unsupervised learning. Supervised learning occurs when there is a target variable that can be predicted by a statistical model. This is typically the case for tax fraud detection, the natural target variable being the amount of tax evasion observed by the tax administration through audits. But unsupervised learning methods are also widely employed in tax fraud detection. Unsupervised means that classification techniques such as decision trees and clustering are used to single out possible outliers displaying aberrant or extreme, and therefore suspicious, behavior. A typical application of this approach is to compare the behavior of a given taxpayer with the average behavior in its industry or area.

One major limitation of this approach however is that it does not make use of the information on observed tax evasion collected through audits.

**Promoting compliance: absolute or relative?**

When promoting compliance - fighting non-compliance - an important distinction is between absolute and relative non-compliance. Absolute non-compliance can be defined as the total monetary value of tax evasion, plus penalties and late interest. This notion of non-compliance is useful when the goal of audit planning is to maximize tax revenue under a fixed audit resource constraint. This approach is the essence of modern RBA.

Relative non-compliance is defined as the ratio of absolute compliance (as defined above) over some measure of the taxpayer's size or total tax due, for example turnover, profit or tax liabilities. This provides a measure of the intensity of individual non-compliance and can also be readily measured based on audit records combined with taxpayers’ attribute data. This approach is useful when the goal is to maximize the number of compliant taxpayers under a fixed audit resource constraint. It is closer in spirit to traditional, pre-RBA strategies, which have often attempted to enforce tax codes uniformly, regardless of revenue optimization. This approach also gives more weight to equity among taxpayers; and stresses the role of audits in educating and informing taxpayers. Another possible benefit is that this approach can help to influence compliance behavior as taxpayers grow from SMEs to larger businesses, and therefore contribute to revenue maximization in the long run.
In practice, tax administrators often use a relative notion of risk for SMEs, while using an absolute notion of risk for larger enterprises. This is because under a pure revenue-maximizing strategy (that is, stressing absolute compliance), most SMEs, however non-compliant they might be individually, would probably not be identified as a priority risk worthy of an audit.

In our experience, the trade-off between revenue maximization on the one hand and equity and educational impact on the other is an issue that is best addressed by each tax administration based on their audit objectives and procedures.
IMPLEMENTATION ISSUES

Random audits vs red flags
The applied literature has long emphasized the benefits of an audit strategy based solely on random audits (Mookherjee and Png 1989). Random audits are by definition unbiased; they are a powerful deterrent against fraudulent behavior; they are efficient in uncovering new techniques of fraud; they are immune to any collusion between auditees and auditors.

In the real world of revenue agencies and insurance companies, however, audit case selection is often based on an assessment of individual risks and the associated deterministic, not random, decisions to audit taxpayers/claimants if and when a red flag is raised. To be sure, random audits are costly – they simply do not focus on the highest risks.

How are theory and practice reconciled? Dionne and al. (Dionne, Giuliano, and Picard 2008) show that when taxpayers or policyholders cannot perfectly control the fraud signals perceived by auditors, an optimal audit strategy is to use red flag audits based on individual risk scoring. This is because in this situation, 'from the auditors’ standpoint, the auditing strategy is deterministic (the optimal audit decision is actually a non-random function of red flags) but is random for the taxpayers or policyholders.'

The recommended best practice (Vellutini 2011b), and the one implemented by Revisor, is to combine a red flag strategy with a healthy proportion of random audits – says 10% of all audits as a rule of thumb.

To sum up, it is not random audits vs red flags but rather random audits and red flags and this is what Revisor does.

RBA and variable selection

The need for efficient variable selection
Models for risk-based audits are all about predicting the potential tax evasion of any taxpayer, given a set of observed characteristics. But how do we pick the right predictors among hundreds of candidate characteristics, for instance turnover, type of activity, number of employees, profit rate, number of years with losses, number of late-filing incidents, profit rate deviation from industry means, etc.?

To the chagrin of statisticians, some tax administrations are content to use so-called international best practice. They just pool a list of risk predictors from other countries’ experience – assuming that they will adequately reflect compliance behavior among their own taxpayers. Red flags are raised when certain thresholds based on informal rules of thumb are crossed, triggering an audit.
Such efforts are not to be sniffed at. There are often the first steps toward a wide-ranging reform of the audit function; in any case they are better than pure manual audit case selection; and are almost always useful in fighting corruption in the tax administration.

However, the major limitation of this approach is that it makes no use of the wealth of data held by any tax administration.

**Predicting, not explaining**

Selecting the risk drivers that accurately predict tax evasion is the key to an efficient data-driven audit case selection process.

First, observe that our primary objective in implementing risk-based audits is not to explain tax evasion but indeed to predict it. As nicely exposed by Galit Shmueli (Shmueli 2010), statistical modelling for the purpose of generating predictions is very different from econometrically testing an underlying explanatory model of causation – a theoretical model. We do not have a list of candidate variables suggested by a theoretical model. We approach the problem from a pure statistical, a-theoretical angle and select whichever variables have the strongest predictive power based on the data at hand.

Secondly, however, a critical consideration is to internalize the trade-off between bias and variance, as made clear by Hastie, Tibshirani and Friedman (Hastie, Tibshirani, and Friedman 2009). In other words, increasing the number of predictors mechanically increases the within-sample predicting power of the model (thereby reducing its 'bias'); unfortunately it also increases its variance: the out-of-sample predicting performance will be negatively affected. Put differently, over-fitting your sample data will cause the model to perform badly when generating predictions on new data (out-of-sample data; data not used to estimate the model).

The good news is that the statistical techniques available to determine the right trade-off between bias and variance have changed dramatically over the last decade.

**Techniques for variable selection**

This last decade has brought a revolution in variable selection techniques and risk-based audits are set to benefit hugely from these advances. Revisor is at the forefront of these innovations. Among the various options available to the analyst, two techniques stand out:

1. **Penalized estimators**, also known as shrinkage methods, have become of critical relevance to the applied statistician. What are they? The gist of penalized estimators is that instead of merely minimizing prediction errors they minimize prediction errors PLUS a penalty which is a function of the model’s raw coefficients. This has proved a very successful approach to finding a prediction model’s optimal balance.
between variance and bias. By explicitly accounting for the variance cost of including additional variables in the model (which reduces the bias but raises the penalty), penalized estimators are today's tool of choice for building efficient prediction models. To name only the most famous penalized estimator from a vast and growing class, the Lasso has made its mark in a number of applied fields.

2. **Cross validation**, although older in its principles, has become tremendously useful to the risk-based audit analyst, especially when used in conjunction with penalized estimators. The idea here is that by partitioning and repeatedly and randomly re-sampling the data used to both estimate and test the model, one can select the variable set that offers the best balance between bias and variance – as assessed from a predictive power angle. In particular, cross validation is used to set the right weight for the penalty in a penalized estimator.

**Scorecards for RBA: to group or not to group?**

**What is grouping?**

Modern risk-based audits rely on scorecards to assign a risk score to taxpayers, and plan audits accordingly. One critical aspect of the construction of a scorecard for RBA is the grouping of characteristic variables.

In classical scorecard methodology, for RBA or otherwise, it is customary to group continuous characteristic variables into just a few levels – typically from 3 to 6 groups, each assigned a determined value of the variable. Various techniques are available for grouping: standard clustering algorithms such as k-means are easy to use and normally robust, although not so efficient to do the grouping as a function of the target variable – an important limitation. Decision trees such as a CART algorithm are better from that angle: they can group characteristic variables as a function of their relationship with the target, which in turn boosts the performance of the scorecard. This is the technique implemented by Revisor.

Grouping categorical characteristic variables can also sometimes be needed (think for example of industry codes with hundreds of modalities) but is more difficult than with continuous variables. Short of using dissimilarity matrices (which amounts to telling the computer which modalities are to be linked together, pair-wise, a tedious and seldom used process in RBA), the analyst can collapse the categorical variables to be grouped by taking the averages (means) of available continuous variables for each modality. He is then left with a collapsed dataset where observations are the modalities and the variables the means of the original continuous variables, and can then apply standard clustering techniques to group the modalities – i.e. k-means or decision trees. Again, this is what Revisor does.
**Why group?**

The initial reaction of the trained econometrician to grouping is to ask: why group variables and potentially lose a lot of information in the process? However, when understood in the proper context, grouping is not to be sniffed at.

First, if each group is associated with a specific dummy, grouping allows for easy, piecemeal non-linear modeling. Say the dummy of the first group carries a positive coefficient and the dummy of the last group a negative one: you have your non-linear model just by grouping variables adequately. Secondly, and more importantly, grouping was developed in environments when managers have little if any statistics/econometrics training. As exposed in the classic Siddiqi (2006), it turns out that grouped variables lead to easy to read scorecards with neat brackets for each variable. If sales are, say, between €354.000 and €845.500, then your score is, say, 122 points.

Scorecards with grouped variables are easily understood and easy to use. This is why we recommend grouping variables by default, as implemented in Revisor.

**The need to address sample selection bias**

Why is sample selection bias a problem in risk-based audit strategies? Sample selection bias arises when the sample used to estimate a model is not drawn randomly from the overall population, but rather is selected on the basis of observable or unobservable characteristics.

This is the case of the typical data used for RBA: audit data is available for those entities which have already been audited at least once, and these entities have generally not been drawn randomly. Audited entities have been picked through the audit planning process as potential high risks.

Sample selection correction is embedded in Revisor, which relies on a special adaptation of the **Heckman two-step procedure** (Heckman 1979). More information can be found in the documentation of Revisor.

**Organizational considerations**

As illustrated below, a key point suggested by successful implementations of risk-based audit strategies is the **separation of the process of selection of taxpayers for audit from the implementation of the audits**. Note that this is not the traditional organization of the audit function, where auditors are responsible for selecting *and* auditing taxpayers,

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1 This section draws on Vellutini (2011b).
especially when the selection is primarily based on manual screening (see below). Separating the two functions brings crucial benefits:

- It helps to fight conflicts of interest and corruption among inspectors as it prevents the targeting of taxpayers based on their potential for side payments and/or protecting corrupt taxpayers from audits.
- It brings economies of scale and gains from specialization from (i) the selection function, which is typically centralized at regional or at national level; (ii) the inspection/audit function itself, where inspectors can be efficiently trained in auditing, as opposed to audit selection.

**Separating Audit Case Selection and Audit Implementation**

A related point is the *incentive scheme* used by tax administrations. International experience suggests that the compensation of auditors should not be directly linked to the volume of audit adjustments and penalties raised by them – as is often the case in pre-risk-based audit approaches. Providing bonuses mechanically indexed on audit results has been shown to: (i) strongly bias audits against taxpayers, undermining the much-needed perception of fairness in the tax system; (ii) further encourage strategic selection behavior (auditors maximizing their bonuses) in environments where the audit selection function is not adequately separated from audit implementation.
REFERENCES


