A Roadmap for Analytics in Taxpayer Supervision

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Abstract: Tax administrations need to become more efficient due to a growing workload, higher demands from citizens, and, in many countries, staff reduction and budget cuts. The novel field of *analytics* has achieved successes in improving efficiencies in areas such as banking, insurance and retail. Analytics, which is often described as an extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions (Davenport and Harris, 2007: 7), fits well in tax administrations, that typically have access to large volumes of data. In this paper we will answer the question how analytics contributes to a *Compliance Risk Management* approach – a major trend in taxpayer supervision in the last decade. The main tasks within compliance risk management include risk identification, risk analysis, prioritization, treatment, and evaluation. The answer of the research question gives more insight in what we can expect from analytics, and will assist tax administrations that want to improve their analytical capabilities. Attention is paid as well to limitations of analytics. Findings include that over half of the activities in taxpayer supervision can be supported by analytics. Additionally, a match is presented between supervision activities and specific analytical techniques that can be applied for these activities. The article also contains a short case study of the Netherlands Tax and Customs Administration on selection of VAT refunds with analytical techniques.

Keywords: tax administration, taxpayer supervision, compliance risk management, analytics and data mining

1. Introduction

Tax administrations need to become more *efficient* due to an expanding workload often combined with staff reduction and budget cuts. Workload increases by a growing number of taxpayers – both private individuals and business - and a rise in dynamics of the taxpayer population (shifting from employment to self-employed and vice versa). In addition workload expands by growing international trade, partly due to new developments in e-commerce (EU, 2011: 2). Another reason to improve efficiency is the rising expectations of citizens that want cheap, high quality government agencies. These rising expectations are partly due to higher education levels of citizens (OECD, 2004a: 9) combined with the experience of better performing non-governmental organizations and businesses.

'Analytics' is a promising candidate for improving efficiency in the administration of taxes. Davenport and Harris (2007:7) define 'analytics' as an 'extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions', and we will follow this definition in our paper. Decisions and actions that result from an analytical approach, have often led to more efficient processes (Davenport and Harris, 2007) in organizations that are similar to tax administrations with respect to their size and activities. Moreover, tax administrations meet an important condition for starting with analytics, namely the availability of data: they generate a lot of transaction data and have access to many third party data. Additionally, tax administrations process huge amounts of money, so even small improvements of their operations can yield substantial (monetary) benefits. It could be argued that - as a side effect - analytics can increase objectivity with respect to the treatment of taxpayers. Note that the development of analytics has been made possible by progress in information and communication technology.

Interest of tax administrations in 'analytics' or 'data exploitation' is therefore evident. Also international bodies like the Organisation for Economic Co-operation and Development (OECD), the European Commission (EC), and the Intra-European Organisation of Tax Administrations (IOTA) have put analytics on their agenda. Moreover, several tax administrations (among others the tax administrations of The Netherlands and the United Kingdom) are investing considerably to reap the benefits of analytics.

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In this paper applications of analytics are limited to *taxpayer supervision* and more specifically to a so-called *Compliance Risk Management approach* – a major trend in taxpayer supervision in the last decade (section 2.1). Taxpayer supervision can be positioned among other activities of a tax administration by considering the following dichotomy. In general, a tax administration has the following two tasks: (1) to make it possible for taxpayers to pay taxes, and (2) to examine whether taxpayers actually paid them. The first task requires a proper organization of internal processes like a tax return filing or tax payment process. The second task requires an adequate supervision process. These two main tasks of a tax administration coincide largely with a distinction made by Davenport and Harris (2007:15). They distinguish between applications of analytics to improve *internal* processes (financial, manufacturing, R&D, and Human Resources) and *external* processes (customer and supplier processes). Note that the term *taxpayer* is used broadly in this paper, as a term for a private individual, a business, a not-for profit or any other legal entity that is taxable.

The objective of this paper is to explore the applicability of analytics in a taxpayer supervision context. In this paper we will answer the question how analytics contributes to a Compliance Risk Management approach. This exploration will lead to more insight into what to expect from analytics in taxpayer supervision and will at the same time give directions to tax administrations willing to improve their analytical capabilities in taxpayer supervision. It also offers some insights to researchers in e-Government with an interest in the potential of analytics for governmental organizations. Attention is also paid to limitations of analytics in taxpayer supervision.

To answer the research question, the terms 'analytics' and 'compliance risk management' are decomposed into underlying techniques and activities, based on the available literature. Subsequently the techniques are mapped to supervision activities, according to their relevance and suitability. To illustrate the practical side of analytics, a short case study is included, in which one of the authors participated.

The paper is organized as follows. Section 2 explores related research. Section 3 sketches current developments in analytics in tax administrations and in the insurance and banking sector. Section 4 describes typical activities in taxpayer supervision and typical classes of analytical techniques. These are subsequently mapped onto each other and a roadmap for analytics in taxpayer supervision is sketched. Section 5 presents a case study of the Netherlands Tax and Customs Administration (NTCA) (NTCA, 2016) aimed at detecting erroneous VAT refunds. Section 6 contains conclusions and a discussion on the further development of analytics in taxpayer supervision.

2. Related research

In this section we look more closely to relevant scientific literature related to the areas of research, supervision and analytics. In 2.1 we briefly discuss theories about modern supervision. Subsequently, in section 2.2 the use of analytics within tax administration is described. Finally, in 2.3, we discuss the managerial literature on analytics.

2.1 Theories about modern supervision

Tax compliance is subject of research for a long time already, starting with the seminal paper of Allingham and Sandmo (1972) in which the economics-of-crime theory was discussed. This theory looks at a taxpayer as a 'homo economicus', deliberately weighing the expected utility before deciding to comply with the tax laws. As a reaction, tax administrations use so-called 'deterrence' strategies, which are based upon the assumption that the threat of detection and punishment enforces compliance. In this view, frequency of audits and size of fines are tools for treating non-compliance. Analytics might contribute to such a strategy, by optimizing the selection of taxpayers for audits, detecting fraud, and calculating optimal values of fines.

However, in practice observed compliance levels proved to be higher than predicted by this early theory. This gave rise to new theories about influencing tax compliance behaviour. These new theories have identified many factors that play a role in the actual behaviour of taxpayers (Andeoni, Erard and Feinstein, 1998), such as psychological factors, personal norms, social norms, tax morale, and opportunities for tax evasion. A review paper of Jackson and Milliron (1986) summarizes tax compliance research in the period 1970 - 1985, while a review paper of Richardson and Sawyer (2001) extends this period towards 2001. A more recent overview is given by Alm (2012). Research showed that 'deterrence strategies' alone are unable to efficiently attain or maintain desired compliance levels (especially given a finite level of resources).

New insights in behaviour generated new ideas about ‘advice and persuade’ strategies. Several scholars from Public Administration have suggested policies for effective supervision, such as the theory of responsive regulation of Braithwaite (2007) and the psychology of persuasion of Cialdini (2004). These policies suggest new instruments for treating non-compliance, like limiting opportunities to make errors or reducing unintentional errors by improving services. Analytics might contribute in such a strategy, for example, by providing a more accurate description of taxpayer behaviour, investigating areas of frequent unintentional errors and detecting taxpayers needs for improving taxpayer services.

The OECD (2004a) and the EC (2010) encourage tax administrations to combine both strategies within a so-called *Compliance Risk Management* approach, in which a tax administration attunes its strategy to the taxpayer’s behaviour. In this paper we will discuss taxpayer supervision from the perspective of tax administrations applying a Compliance Risk Management approach.

2.2 Analytical applications within tax administrations

The authors could track fourteen articles published in scientific journals aiming at improving efficiency of taxpayer supervision with analytical techniques. These articles focus on applying specific techniques. Articles treating ‘analytics’ as a general concept within tax administrations were not found.

Eleven of these publications focus on audit selection. The techniques used follow developments in computer science and statistics. Publications from the 1980s treat predominantly techniques from statistics and econometrics that require limited computations. The rise of computer power in the 1990s, got computer scientists interested in extracting knowledge from data as well. Publications on audit selection from that period onwards, focus on these newer techniques.

Several studies report an increasing yield of audits by using analytics in the selection process. Hsu et al. (2009: 25) report a significant increase in efficiency (63%) compared to the manual selection of audits in Minnesota (USA). Gupta and Nagadevara (2007: 387) report an increase of the 'hit rate' of up to 3.5 times compared to random audit selection of VAT returns in India. Wu et al. (2012: 8777) claim an improved accuracy compared to a manual process in Taiwan. Da Silva, Carvalho and Souza (2015: 227) conclude that results are very promising for the tax administration, when studying audit selection for tax refunds in Brazil. In spite of these successes, analytical techniques for audit selection are still often used in isolation and not fully embedded in the supervision processes.

2.3 Managerial literature on analytics

Analytics has received much attention in the managerial literature since the appearance of the book ‘Competing on Analytics’ (Davenport and Harris, 2007). Davenport and Harris point out that analytics is more than a mere collection of techniques; by adopting a strategy of incorporating these techniques consistently in decision making processes, a competitive advantage can be created. Since then, the managerial aspect of analytics has been the subject of many articles. Many of the findings and developments on the managerial aspect, along with some concrete examples, can be found in the subsequent books of Davenport (Davenport, Harris and Morison 2010 and Davenport, 2014). Recently, review articles have been appearing, reviewing the managerial literature on analytics for sectors like Supply Chain Management (Wamba and Akter, 2015) or E-commerce (Akter and Wamba, 2016). Coverage of analytics in government has been relatively weak.

3. Practical Experiences with Analytics

In this section practical experiences with analytics are discussed. General experiences of tax administrations, based on the results of an OECD survey, are discussed in 3.1. In 3.2 we focus on the experiences in the banking and insurance sector, which can be seen as a ‘frontrunner’ in the use of analytics.

3.1 General experiences of tax administrations

In 2016 the OECD, Forum on Tax Administration (FTA) issued the report *Advanced Analytics for Better Tax Administration* (OECD, 2016), which provides practical examples of how tax administrations are currently using advanced analytics. OECD describes ‘Advanced analytics’ as “the process of applying statistical and machine-learning techniques to uncover insight from data, and ultimately to make better decisions about how to deploy resources to the best possible effect”. Especially the use of statistical techniques to make inferences about cause and effect is interesting for those tax administrations that apply a *Compliance Risk Management* strategy in which they try to influence taxpayer behaviour to comply with fiscal rules. The report states that advanced analytics is *proving* an extremely valuable tool in improving tax administration *effectiveness*, meaning that it allows tax administrations to achieve its goals (as e.g. a higher level of compliance) in a better way compared to the situation not using advanced analytics. The report however does not make any assessment and practical examples only limitedly support the proof of this statement.

The OECD report (OECD, 2016) is based upon a survey, which is completed by 16 FTA members, one of which is the Netherlands. Areas identified – in which advanced analytics are used – are: audit case selection, filing and payment compliance, taxpayer's services, debt management and policy evaluation. According to the survey Australia, Ireland, New Zealand, Singapore, the United Kingdom and the United States use advanced analytics in all areas mentioned. The Netherlands uses advanced analytics in audit case selection and debt management. Almost all respondents appear to use advanced analytics to improve audit case selection. In the other areas the use of advanced analytics seems to be less (structurally) used. Unfortunately, the survey is less specific about the extent of applying analytical activities; are we observing isolated analytical applications or is analytics fully embedded in the culture of the organization?

The OECD report (OECD, 2016) concludes that in the normal day-to-day work tax administrations are constantly making predictions and coming to conclusions about the likely impact of their activities. Advanced analytics – in the opinion of the OECD - does not aim to achieve anything fundamentally new, but it seeks to carry out these same tasks with more reliance on data and less on human judgment.

Currently the focus of most tax administrations seems to be more on *efficiency* of processes rather than *effectiveness* of supervision. Most tax administrations that use advanced analytics for audit case selection seem to aim to improve the identification of tax returns or refunds/claims that might contain errors or be fraudulent. In terms of using 'predictive' analytics the current way of working does therefore seems to 'predict' that a tax return contains a problem, but not (yet) seems to be able to anticipate likely problems.

3.2 Practical experiences in banking and insurance

Analytical techniques entered the banking and insurance sectors relatively early - in the late 90's. Simple predictive models like logistic regression or decision trees were used to address marketing problems like mailing selection, cross- and up-selling, credit scoring, and improving customer retention (Linoff and Berry, 2011). Simple cluster analysis techniques were used to partition clients into homogenous groups. Also in this period, the first successful application of neural networks in the banking sector took place: the Hecht Nielsen Company developed a system for detecting fraud with credit card transactions, (Hassibi, 2000).

Over time the usage of analytics in banking and insurance has been expanding, resulting in better management of data, more powerful data analysis tools, and automation of typical analytical tasks like data pre-processing, model building, and model maintenance. However, the main areas of applications of analytical techniques have not changed: marketing, fraud detection and risk management. It is estimated that currently in the banking sector the ratio of advanced analytics to basic business intelligence, meant as analyzing historical data with data warehousing methods, is like 72% to 28% (Kumar et al., 2016: 20).

Recently, banking and insurance sectors apply analytics to risk adjusted pricing, where the objective is to determine the price of a loan or an insurance policy according to the estimated risk of the individual client. This approach, due to some controversies around it, like privacy issues, is still not very popular (Acebedo and Durnall, 2013). For example, some insurance companies offer so-called "user-based" car insurance, where the insurance fee is determined by the driving style that is measured by dedicated devices installed in a car (Lieber, 2014). Insurance companies also use more and more social media like Facebook or Twitter to detect fraud by comparing client's claims to the information the client makes publicly available (Shane, 2016).

4. Analytics for taxpayer supervision

In this section we look more closely how analytics can contribute to taxpayer supervision when tax administrations are applying a Compliance Risk Management approach. In 4.1 a brief explanation is given of various activities that tax administrations apply in taxpayer supervision. Subsequently, the technical side of analytics is unraveled in 4.2 by providing an overview of modern analytical techniques. Next, in 4.3, activities and techniques are mapped onto each other, leading to our first findings. Finally, in 4.4, a roadmap for applying analytics in taxpayer supervision is sketched.

4.1 Activities in taxpayer supervision

Modern taxpayer supervision is designed according to a so-called Compliance Risk Management approach. The objective of applying Compliance Risk Management is to facilitate management of the tax administration to make better decisions. The Compliance Risk Management process helps to identify the different steps in the decision-making process. The five major steps are (EC, 2010: 8): risk identification, risk analysis, prioritization, treatment and evaluation. The first step, risk identification, aims to identify specific compliance risks that a tax administration encounters. Compliance risk is here understood as a risk of a taxpayer failing to comply with the obligations of the tax law. In the second step, risk analysis, the impact of the identified risks is assessed. Moreover, the causes of the risks are examined. In the third step, prioritization, decisions are made about supervision activities that match the causes of the identified compliance risks/taxpayer behaviour. Prioritization is needed since resources for treating risks are scarce. In step four, treatment, execution of an agreed approach takes place. In step five the effects of the treatments (and policies) are evaluated to improve future decisions.

In general, different organizational units within a tax administration perform the activities related to these five steps. *Table 1* shows the steps and the organizational unit that could perform the related activities.

Table 1: Main steps in compliance risk management and typical departments involved

Steps in Compliance Risk Management	Risk identification	Risk Analysis	Prioritization	Treatment	Evaluation
Department involved	Staff	Staff	Management	Operations	Staff

If each of the five steps contains activities that can be supported by analytics - to a varying degree - a comprehensive, analytical approach to taxpayer supervision will not be restricted to one particular organisational unit within a tax administration. In *table 2* we will have a more detailed look at the activities in the various stages.

Table 2 lists the main activities for each step following the EU and OECD guides on Compliance Risk Management (EU, 2010) and (OECD, 2004a), and classifies the activities according to the estimated value of analytics to them. The classification is based upon an estimation made by the authors based upon their experience. Limitations arise, as a complete overview of activities is not available. Moreover activities are not weighted in relation to importance for Compliance Risk Management.

Table 2: Activities in taxpayer supervision that can be supported with analytics

(H = High, M = Medium, L = Low)

Step	Activities supported by analytics	Activities with (almost) no role for analytics	Level of activities supported
Risk Identification	Horizon scans	Society support	M
	Random audits	New legislation	
	Identify new risks from data	Information from other tax administrations	
	Segmentation of taxpayers	Third party information	
	Detecting Fraud	Signals from the shop floor	

Step	Activities supported by analytics	Activities with (almost) no role for analytics	Level of activities supported
Risk Analysis	Quantify risks with in-house or external data		H
	Hit rate scoring		
	Random audits		
	Tax gap estimations		
	Trend analysis		
	Root-cause analysis		
	Estimating costs of treatment		
Prioritization	Calculating human and other resources	Assessing political and social effects of risks	L
	Optimizing resource allocation	Developing criteria to prioritize	
		Matching causes (of risks) and instruments	
Treatment	Easy contacts	Risk transfer to other parties	L-M
	Desk audits	Changing legislation	
	Field Audits	Consultation and agreements	
	Administrating in the cloud	Fiscal education	
	Real-time checking of tax returns on risks and inconsistencies	Understandable legislation, tax returns and support information	
	Pre-filled tax returns	Advance ruling	
		Inventing new treatment options	
		On site visits	
Evaluation	Outcome measurement	Plan evaluation	M
	Experimental Design of evaluation	Process evaluation	

Looking at *table 2*, it seems safe to state that in all stages of the Compliance Risk Management approach analytics can play a role. A substantial number of activities, especially in risk identification, risk analysis and evaluation can be supported by analytics. It is also noteworthy to observe that for a substantial number of activities analytics (currently) does not seem to have an added value.

A common misunderstanding is that analytical algorithms can solve business problems autonomously. According to Daniel Larose (2005: 4), this misunderstanding is partly caused by software vendors that, '… market their analytical software as being plug-and-play out-of-the-box applications that will provide solutions to otherwise intractable problems without the need for human supervision or interaction'. In reality, analytical experts are needed to guide the computer algorithms. Moreover, domain experts are crucial for drawing right conclusions from the output of the techniques. For instance, in risk identification, analytics does not come up with a fiscal risk directly. It mostly points to irregularities that *might* lead to a new fiscal risk when studied by a domain expert. Therefore, it is essential to realize that analytics will always need to depend on support of human experts.

4.2 Classes of analytical techniques

In this section, analytical techniques are grouped by the task they perform. The grouping is a result of comparing several categorizations found within textbooks covering applications of analytics (Federer, 1991; Cramer, 2003; Linoff and Berry, 2011; Larose, 2005; Liu, 2007; Leskovec, Rajaraman and Ullman, 2014). In order not to get lost in details, we have merged some classes of analytical techniques. This holds especially for 'descriptive statistics' and 'mining new data sources'. As a result, we distinguish the following ten major classes of analytical techniques that are frequently seen in taxpayer supervision:

Table 3: Overview of classes of Analytical techniques

Classes of analytical techniques	
1. Descriptive statistics	6. Time series analysis
2. Experimental design	7. Anomaly detection
3. Hypothesis testing	8. Recommendation systems
4. Predictive modelling	9. (Social) Network analysis
5. Cluster analysis	10. Mining new data sources

(1) *Descriptive statistics.* Techniques used for descriptive statistics provide basic insights by calculating simple summary statistics, visualizing data, or eliminating non-informative data. The latter is often called data reduction, or feature extraction. These techniques can be highly effective, despite their simplicity, and are broadly applicable. Typical techniques in this class are the construction of frequency tables or computing means and standard deviations. Also plotting histograms, bar charts and scatterplots are frequently employed. Factor analysis is a popular technique for data reduction (Federer, 1991: chapter 9 and 10; Cramer, 2003: chapter 2). In taxpayer supervision descriptive statistics are used e.g. for determining the number of non-compliant taxpayers and the amount of lost money due to (compliance) risks.

(2) *Experimental design.* To gain specialized knowledge, surveys and experiments are often needed. Experimental design techniques assist in setting up experiments that gain maximal knowledge, while limiting the number of observations to be examined. Typical techniques include sampling designs and designs for controlled experiments, such as block designs (Federer, 1991: chapter 7). In taxpayer supervision experimental design can help to design random audit programs that provide more information on risks of a whole population by auditing a sample of taxpayers of that population. Another application is to design an experiment in which taxpayers are exposed to different treatments to find the most effective treatment.

(3) *Hypothesis testing*. Hypothesis testing is used to test whether an assumption (for instance about the behavior of a group of taxpayers) is supported by the data. In taxpayer supervision this often means checking prior assumptions of experts concerning risks. Typical techniques include statistical tests like the Chi-square test, the F-test (implicitly used in ANOVA), or some non-parametric tests.

(4) *Predictive modelling.* Predictive modelling is used to predict a characteristic (called 'target') of a taxpayer or a tax return, with help of a model. For example, in case of tax returns, this characteristic is often defined as true or false, depending on whether the tax return contains a particular error or not. The model is automatically generated by a computer algorithm based on a systematic examination of historical cases with a known target. An analyst selects a suitable algorithm and sets the parameters of the algorithm. Some well-known modelling techniques are decision trees, logistic regression, discriminant analysis, k-nearest neighbours, neural networks, support vector machines, and random forests (Hastie, Tibshirani and Friedman, 2008: chapter 2)..

(5) *Cluster analysis.* Techniques for cluster analysis are used to group similar taxpayers or tax returns. This grouping gives more insight and allows tailored supervision approaches. Frequently used clustering techniques include K-means, BIRCH, and DBSCAN (Cramer, 2003: chapter 4; Liu, 2007: chapter 4).

(6) *Time series analysis.* Techniques for time series analysis are applied to find patterns in measurements that are registered periodically. For instance, techniques can be applied to find a trend or a seasonality impact within monthly sales that are reported in tax returns. Typical techniques are ARMA, ARIMA, or Kalman filters.

(7) *Anomaly detection.* Anomaly detection aims to find unexpected observations or events that deviate significantly from normal patterns. In taxpayer supervision these unusual patterns can lead to the detection of fraud, but anomaly detection can also be used to find unknown risks. Often anomaly detection proceeds by first modelling normal behaviour (by applying predictive modelling techniques or cluster analysis) and subsequently defining a measure ('distance') of abnormality to identify anomalous observations. A classical technique in tax administrations and accounting is Benford's law.

(8) *Recommendation systems.* Recommendation systems recommend new products to customers based on the analysis of implicit or explicit preferences of these customers, reflected in their buying behavior or ratings they give to products. This field has grown substantially with the rise of e-commerce. Recent techniques that can construct recommendation systems are collaborative filtering and matrix factorization (Linoff and Berry, 2011: chapter 9; Leskovec, Rajaraman and Ullman, 2014: chapter 9). Another well-known technique for constructing simple recommendation systems is the A-Priori algorithm (Leskovec, Rajaraman and Ullman, 2014: chapter 6). Techniques from recommendation systems are not yet applied in taxpayer supervision, but could be helpful for improving taxpayer services or gaining insight in combinations of risks.

(9) *(Social) Network analysis.* Techniques used for network analysis can be applied to extract information or risks from a (social) network of a taxpayer. Applications are found in fraud detection, among others, where the network of a fraudster can reveal new fraudsters. Network analysis is also applied when analysing social media or complicated legal structures of businesses (Liu, 2007: chapter 7; Leskovec, Rajaraman and Ullman, 2015: chapters 5 and 10).

(10) *Mining new data sources.* Last decade, the machine learning community has put considerable effort in extracting information from data sources that are not typically organized in databases or surveys. Examples are collections of documents, images, webpages, twitter accounts, and recorded speech. Special techniques have been developed to tackle these new data sources (Liu, 2007: chapter 6; Leskovec, Rajaraman and Ullman, 2014: chapter 3). In taxpayer supervision these techniques may be used for instance to find unregistered Internet companies.

Note that the (classes of) techniques above often require data preprocessing techniques, like data warehouse technology.

4.3 Matching supervision activities and analytical techniques

The classes of analytical techniques from section 4.2 can be mapped onto the supervision activities of section 4.1, resulting in *table 4*. The table is constructed by carefully questioning whether a class of analytical techniques can contribute to each supervision activity. This mapping is constructed based on practical experiences from the NTCA or known applications in related fields such as marketing or fraud detection.

Table 4: Mapping of (classes of) analytical techniques onto tasks of taxpayer supervision.

Supervision activities and classes of analytical techniques	Descriptive statistics	Experimental design	Hypothesis testing	Predictive Modelling	Cluster analysis	Time series analysis	Anomaly detection	Recommend. Systems	(Social) Network Analysis	Mining new data sources
1. Risk Identification										
Horizon scans	X		X			X	X			X
Random audits	X	X	X							
Identify new risks from data	X					X	X			X
Segment the population of taxpayers	X			X	X					
Detecting fraud				X			X		X	
2. Risk Analysis										
Quantify risks with help of in-house or external data	X									
Hit rate scoring			X	X						
Random audits	X	X	X							
Tax gap estimations	X	X		X		X				
Trend analysis						X				
Root-cause analysis	X	X	X							
Estimating costs of treatment	X									
3. Prioritization										
Calculating human and other resources	X									
Optimizing Resource allocation	X			X						
4. Treatment										
Easy contacts	X			X	X			X		X
Desk audits	X			X			X			
Field Audits	X			X			X			X
Real-time checking of tax returns			X	X	X	X	X	X		
Pre-filled tax returns	X									
Administrating in the cloud				X			X			X
5. Evaluation										
Evaluation analysis			X	X						
Experimental design of evaluation		X								

Descriptive Statistics is the most applicable class of techniques in taxpayer supervision, according to *table 4.* This corresponds with practical experience that a smart summary of the raw data can offer already important insights. Predictive modelling ranks second. Predictive modelling techniques derive their strength from generalizing precious information, typically available for a small group, to all taxpayers. Think for instance about certain information about non-compliance that is only known for audited cases.

4.4 A roadmap for analytics in compliance risk management

Davenport and Harris sketch five developmental stages of an analytical business: (1) *analytical impaired*, (2) *localized analytics*, (3) *analytical aspirations*, (4) *analytical companies*, and (5) *analytical competitors* (Davenport and Harris, 2007). These stages are to a large degree recognizable for tax administrations, although tax administrations lack the competitive framework of businesses.

(1) The first stage, 'analytically impaired', is characterized by businesses making decisions based on intuition only. Data is generally missing or poor and not integrated at this stage, and analytical processes are lacking. Stage one is recognizable for some tax administrations in developing countries where basic administrative processes of the government (company/citizen/property administration) are not in place yet or data is not available in digital form. According to Davenport, Harris and Morison (2010: 185-186) a business can overcome stage one by targeting 'low hanging fruit', i.e. identifying small-scaled projects that show business potential. In taxpayer supervision one may think about finding and testing basic audit selection rules for a risk for which data can be made available. Another possibility is acquiring and matching third party data with data of the tax administration. At the taxpayer service side, one may start with registering and analyzing the type of questions that arise by taxpayers to get a better understanding on bottlenecks they experience.

(2) The second stage, 'localized analytics', is characterized by autonomous analytical activity by individuals or disconnected teams within a business. Business wide agreement on definitions is generally missing, so 'multiple versions of the truth' may exist. In niches however, isolated analysts might have achieved some nice tactical results. Nowadays many tax administrations are in this stage, which may be caused by decentralisation combined with a large number of employees within tax administrations. In such a setting, a strong effort from senior executives is needed to create a cohesive system of analytical activities. This is in agreement with the observation of Davenport and Harris (2007: 114). At the moment, however, interest in analytics of senior executives in tax administration is growing in many countries.

(3) The third stage, 'analytical aspirations', can be achieved by building business consensus around analytical targets, starting to build a business analytical infrastructure, create a business vision on analytics, target business processes that cross departments, and recruit analysts (Davenport, Harris and Morison, 2010: 185-186). Many of these transitional activities have been observed in the previous years in tax administrations like in the United Kingdom and The Netherlands. The third stage is characterized by coordinated analytical objectives, separate analytical processes, analysts in multiple areas of business, early awareness and support of analytical possibilities among executives, and a proliferation of BI-tools. For taxpayer supervision this stage means that at least some activities mentioned in *table 4* are supported by analytics. By integrating external data, establishing business governance of technology and an analytical architecture, engaging senior leaders, working with main business processes, and developing relationships with universities and associations, the fourth stage can be reached.

(4) In the fourth stage, high quality data is in place as well as a Business Information plan. Some analytical processes have been embedded in the business processes, and broad executive support is in place. Change management is applied to build a fact-based culture. In this stage, most of the supervision activities mentioned in *table 4* are supported by analytics. Moreover, analytics does not only bring insights into taxpayer supervision, but it is also structurally embedded in the compliance risk management strategy. For example, identification of compliance risks and analysis of trends as well as root-cause analysis takes place structurally, per segment of taxpayers, enabling a tax administration to match the results with the appropriate treatment per (group of) taxpayer(s).

(5) The fifth stage is characterized by deep strategic insights, fully embedded analytical applications, highly professional analysts, a CEO with passion for analytics, a broadly supported fact-based and learning culture and a business wide architecture. No tax administration has yet reached this stage, and it might not be the ambition of all tax administration to develop analytics to this extent.
The transition from the second stage to the third stage is probably the most interesting for tax administrations. We now present a case study that highlights issues involved in such a transition.

5. Case Study: VAT refund risk model

The Netherlands Tax and Customs Administration (NTCA) receives numerous VAT refunds requests annually. These requests, if approved, result in a payment of the NTCA to a taxpayer. All VAT refunds are automatically checked against risk rules to select risky VAT refund requests. If the risk rules flag a VAT refund as risky, a manual inspection follows.

In 2014, the NTCA started a project aiming at replacing current risk rules – designed by domain experts – by a risk model, constructed by applying predictive modelling techniques. Both the old risk rules and the new risk model take advantage of domain knowledge and available data. The main difference however, is that with the old risk rules hypotheses about risky features emerged in the minds of domain experts. With the new risk model, these hypotheses are generated by a computer algorithm and subsequently tested on historic data. Although many of the hypotheses generated by the computer algorithm could be of inferior quality compared to hypotheses of the domain experts, the computer is able to generate much more hypotheses (and more complex ones). The subsequent testing of these many hypotheses on historic data could show some hypotheses that might outperform the old risk rules.

Before the start of the project, some important developments had taken place in the NTCA. The government of the Netherlands approved a program to address structural issues in the operating model of the NTCA, called Investment Agenda (IA). The aim of the IA is providing the necessary response to changing taxpayer's expectations and major technological developments. Within this context a general trend towards centralization had started. Moreover, an awareness of the potential of analytics among a small group of senior and middle management had spread. The IA made it possible to invest in analytics in a time of budget cuts. A small department ('Data & Analytics') was created that had to work on realizing 'data fundaments' and that started several projects, among them the VAT refund project.

The VAT refund project consists of four stages; exploration phase, lab phase, pilot phase, and full implementation phase. Each phase is separated by a go/no go decision, taken by a steering committee involving senior management. Currently (2016) the project has almost completed its pilot phase.

The exploration phase aimed at estimating the financial benefits of the project, the impact on processes, the required changes in ICT and the required efforts of analysts. This phase was followed by the lab phase, where an operating risk model was developed within three months, assisted by an external consultancy firm. Although this first risk model showed promising results on historic data, it was not mature enough to be applied in operations. In the exploration and in the lab phase approximately three analysts of the NTCA were involved. They formed the *development team*.

After the lab phase, the pilot phase started. The aim of this phase was to adapt the risk model that was developed in the lab phase and to test it in practice. Two of in total nineteen local tax offices were appointed to carry out the pilot. In this phase, the development team (now four analysts) was extended with some (VAT) process experts. Moreover, a small *production team* (two people) was formed with the task of streamlining the initial (not very efficient) code to make it suitable for running in production on a daily basis. Also, a *pilot support* team was formed (two people) to support the two pilot locations on the job.

It took three pilots of each three months to come to a risk model that was able to deliver the expected results. In the first pilot, for example, it was noted that although the risk model was good at selecting VAT refunds that contained an error, the selected cases appeared to be merely VAT refunds that contained small amounts. In the second pilot the model was adjusted to select VAT refunds that contained errors, in which substantial amounts of money were involved. At the end of the pilot phase the ICT department became involved because the pilot showed that introducing a new workflow system could further optimize the VAT refund supervision process.

During the pilot phase some unexpected side results were obtained as well. For instance, the riskiness of VAT refunds appeared to deviate substantially between the two pilot locations. This suggested to shifting part of the workload from one location to the other. Some insights could lead to process changes and some gave directions for follow-up projects.

6. Conclusions and points for discussion

6.1 Conclusions on how analytics contributes to Compliance Risk Management

Analytics seems to be a serious candidate for making taxpayer supervision more efficient and more effective. To answer the research question *how analytics contributes to a Compliance Risk Management approach*, the terms 'analytics' and 'compliance risk management' were decomposed into underlying analytical techniques and supervisory activities. Mapping the analytical techniques to the supervisory activities in the various stages of a Compliance Risk Management approach showed the potential for taxpayer supervision. Nevertheless also a substantial number of activities that (currently) hardly could be supported by analytics was found. Our inventory *table 2* suggests that for taxpayer supervision about half of the activities can be supported by analytics. Based upon this inventory it could be argued that governmental activities can be split into those that can be improved by applying analytics and those that cannot.

Although the OECD survey gives practical examples of applying analytics for *audit case selection, filing and payment compliance, taxpayer's services, debt management and policy evaluation*, the focus currently seems to lie on improving selection for tax auditing (higher hit rate, more revenue). Our case study supports the idea that audit selection can be substantially improved with analytics. However, there is a risk in paying too much attention to audit selection with analytics. An increasing attention for analytics may implicitly shift the balance (between prevention and repression) that is needed in a Compliance Risk Management approach from prevention to repression. This effect may occur since applications of analytics on the repressive side (e.g. audit selection) currently are more mature compared to applications on the preventive side (e.g. improving services). The effect may be cancelled by putting more efforts in developing preventive applications.

If we combine the five developmental stages of an analytical business: *analytical impaired, localized analytics, analytical aspirations, analytical companies, and analytical competitors* with the results of the OECD survey, it seems that most tax administrations are still in an early stage of development of applying advanced analytics for Compliance Risk Management, although some tax administrations state that they broadly apply analytics. However, it is not clear from the OECD survey to what extent these administrations apply analytics structurally.

Analytics in our opinion does not achieve anything fundamentally new when it comes to *type of activities* carried out by a tax administration. However, analytics could improve the foundation for a Compliance Risk Management approach, leading to more rational decisions made by management of a tax administration. Analytics, from that perspective, complements *Compliance Risk Management* being a modern strategy for taxpayer supervision. Especially when tax administrations succeed in using statistical techniques to draw predictions and make inferences about cause and effect, analytics will have an added value for Compliance Risk Management - influencing taxpayer behaviour to comply with the rules. Before we really can confirm that analytics is not only more efficient but also more effective for Compliance Risk Management, a proof is needed and therefore tax administrations are urged to measure the impact of their (analytical) activities.

6.2 Discussion points

Although 'analytics' is a promising candidate for improving efficiency and efficiency of the administration of taxes, this paper also shows that in general 'analytics' is in a developing stage with regard to the applicability for tax administrations. Still a lot of issues arise that need further discussion: e.g. with regard to the 'autonomy' of analytics, the scope (or limits) of analytics and privacy aspects.

(1) For supporting supervisory activities with analytics, cooperation seems to be necessary between various staff: analysts, people from the shop floor, process experts and experts in supervision. Analysts need to understand the data and processes by talking with domain experts to avoid serious mistakes. Moreover, experts are needed to judge the (initial) analytical results. Cooperation between analysts and experts is needed in any stage, but is indispensable in the initial, developmental stage.

(2) An obvious limitation of analytical techniques is that one cannot get insights out of data that are not present in the (historical) data. This occurs e.g. when risks related to new legislation pop up. These risks will not be detected by analytical techniques that base themselves on data of the past. However, even without new risks, a certain limit in predictability always exists in data. In statistics and machine learning this is termed

the *irreducible (prediction) error*. This limit on predictability shows itself most clearly, when we observe two taxpayers with identical database records (not containing data on level of compliance), one behaving compliant while the other does not. We cannot expect a computer algorithm to distinguish these cases, as these taxpayers are identical from the computer's viewpoint. Unfortunately, the irreducible error can be quite considerable in many taxpayer supervision applications, limiting the predictability. However, we should not forget that improving predictability with a few percentage points already can be very advantageous for the efficiency of tax administrations dealing with huge amounts of money.

(3) Privacy issues and ethical issues are of concern when applying analytics in a tax administration context. Important guidelines on these issues within the NTCA include making a clear purpose specification that is in line with the right legal basis before starting an analysis. Moreover data used should be proportional to the stated purpose. Some characteristics like religion, race, political preference and health, among others, are explicitly excluded from an analysis. The research community is also researching methods that allow data analysis, while preserving the privacy of individuals (Haddadi et al, 2012). This field is known as 'privacy preserving data mining'. Although some algorithms have been proved to preserve the privacy, care should still be taken to manage the whole process adequately.

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