2 Analytics in Taxpayer Supervision

In this chapter opportunities for applying analytics within taxpayer supervision (also known as 'compliance risk management for tax administrations') are explored. The research in this chapter is guided by the research question:

> **Research Question** *What data science / analytical techniques can be used in* taxpayer supervision *and what contributions may be expected from these techniques?*

The general idea of applying analytics is made more concrete for taxpayer supervision by explicitly writing down the tasks of taxpayer supervision and the techniques known from analytics and data science. This will lead to more insight into what we may expect from analytics and will assist tax administrations that want to improve their analytical capabilities. Also, an overview is given of the current state of analytics in tax administrations. Attention is paid as well to the 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 chapter also presents a short case study of the Netherlands Tax and Customs Administration on the selection of VAT refunds. The chapter is based on the following articles:

- M. Pijnenburg and W. Kowalczyk. Applying analytics for improved taxpayer supervision. In *Proceedings of 16th European Conference on e-Government ECEG 2016*, pages 145–153. Academic Conferences and publishing limited, 2016

- M. Pijnenburg, W. Kowalczyk, E. van der Hel-van Dijk, et al. A roadmap for analytics in taxpayer supervision. *Electronic Journal of e-Government*, 15:19–32, 2017

2.1 Introduction

2.1.1 Research objective

In this chapter we investigate what analytical / data science techniques can be used in taxpayer supervision and what contribution may be expected from these techniques. Several theories exist on how to effectively supervise taxpayers, see Section 2.2.1. In this chapter we will focus on *compliance risk management*, a modern theory about taxpayer supervision that is adopted by many western tax authorities.

The investigation will 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 interest in the potential of analytics for governmental organizations.

To reach the research objective, the terms 'analytics' and 'taxpayer supervision' 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.

2.1.2 Need for more effective taxpayer supervision

Taxpayer supervision needs to become more effective 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 businesses – and a rise in dynamics of the taxpayer population (e.g. shifting from employment to self-employed and vice versa). Moreover, the workload of taxpayer supervision expands by growing international trade, partly due to new developments in e-commerce [62, 41]. Another reason to improve the effectiveness of taxpayer supervision is the rising expectations of citizens that want cheap, high-quality government agencies. Rising expectations of citizens are partly due to higher education levels [41] combined with the experience of smoothly operating non-governmental organizations and businesses.

'Analytics' is a promising candidate for improving the effectiveness in taxpayer supervision. Davenport and Harris [32] define 'analytics' as *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 this chapter. Decisions and actions that result from an analytical approach have often led to more effective processes [32] in organizations, that are similar to tax administrations concerning their size and activities. Moreover, tax administrations meet an essential condition for starting with analytics, namely the availability of data: tax administrations generate many transaction data and have access to much third-party data. As a side effect, analytics may increase objectivity of the treatment of taxpayers.

The interest of tax administrations in ‘analytics’ or ‘data exploitation’ is therefore evident. 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.

2.1.3 Scope of the research

In this chapter, applications of analytics are restricted to taxpayer supervision. We may position taxpayer supervision 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 paid them. The first task requires a proper organization of internal processes like a tax return filing process and a 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 [32]. They distinguish between applications of analytics to improve internal processes (financial, manufacturing, Research & Development, and Human Resources) and external processes (customer and supplier processes). As taxpayer supervision is an external process, we will leave out internal processes in this chapter.

Note that the term ‘taxpayer’ is used broadly in this chapter, as a term for a private individual, a business, a corporation, or any other legal entity that is taxable.

2.1.4 Organization of this chapter

The chapter is organized as follows. Section 2.2 explores related research. Section 2.3 sketches current developments in analytics in tax administrations and the insurance and banking sector. Section 2.4 describes everyday activities in taxpayer supervision and regular classes of analytical techniques. The techniques are subsequently mapped onto the activities and a roadmap for analytics in taxpayer supervision is sketched. Section 2.5 presents a case study of the Netherlands Tax and Customs Administration (NTCA) aimed at detecting erroneous VAT refunds [14]. Section 2.6 contains conclusions, and Section 2.7 provides a discussion on analytics in taxpayer supervision.

2.2 Related Research

2.2.1 Theories about modern supervision

There exists a rich literature about tax compliance, starting with the seminal paper of Allingham and Sandmo (1972) [5] in which the authors discuss the economics-of-crime theory. This theory looks at a taxpayer as a 'homo economicus', deliberately weighing the expected utility before deciding to comply with the tax laws (or not). Therefore, tax administrations use so-called 'deterrence' strategies, based upon the assumption that the threat of detection and punishment enforces compliance. In this view, the frequency of audits and the 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 empirical fact gave rise to new theories about influencing tax compliance behavior. These new theories have identified many factors that play a role in the actual behavior of taxpayers (Andeoni, Erard and Feinstein, 1998 [7]), such as psychological factors, personal norms, social norms, tax morale, and opportunities for tax evasion. A review paper of Jackson and Milliron (1986) [55] summarizes tax compliance research in the period 1970 - 1985, while a review paper of Richardson and Sawyer (2001) [99] extends this period towards 2001. Alm (2012) [6] gives a more recent overview. 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 behavior generated new ideas about 'advice and persuade' strategies. Several scholars from Public Administration have suggested policies for adequate supervision, such as the theory of responsive regulation of Braithwaite (2007) [20] and the psychology of persuasion of Cialdini (2004) [27]. 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 to such a strategy, for example, by providing a more accurate description of taxpayer behavior, investigating areas of frequent unintentional errors, and improving taxpayer services.

The OECD [41] and the EC [38] both encourage tax administrations to use both these strategies within a so-called Compliance Risk Management approach, in which a tax administration attunes its strategy to the taxpayer's behavior. In this paper we will discuss taxpayer supervision from the perspective of tax administrations applying a Compliance Risk Management approach.

2.2.2 Analytical applications within tax administrations

A literature search by the author at the beginning of 2017 has identified fourteen published articles in scientific journals aiming at improving the effectiveness 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 publications treat audit selection. The techniques 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 attracted computer scientists to the topic of extracting knowledge from data. Publications on audit selection from that period onward, focus on these newer, computation-intensive techniques.

Several studies report an increasing yield of audits by using analytics in the selection process. Hsu et al. [54] report a significant increase in efficiency (63%) compared to the manual selection of audits in Minnesota (USA). Gupta and Nagadevara [45] 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. [113] claim an improved accuracy (i.e. less false negatives and / or less false positives) compared to a manual process in Taiwan. Da Silva, Carvalho, and Souza [30] conclude that results are auspicious for the tax administration when studying audit selection for tax refunds in Brazil.

2.2.3 Managerial literature on analytics

Analytics has received much attention in the managerial literature since the appearance of the book 'Competing on Analytics' by Davenport and Harris in 2007 [32]. In the book, 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 [33], [31]. Recently, review articles have been appearing, reviewing the managerial literature on analytics for sectors like Supply Chain Management [109] or E-commerce [4]. The coverage of analytics in government has been relatively weak.

2.3 Practical Experiences with Analytics

2.3.1 General experiences of tax administrations

In 2016 the OECD, Forum on Tax Administration (FTA) issued the report 'Advanced Analytics for Better Tax Administration' [40], which provides practical examples of how tax administrations are currently using advanced analytics, see also section 1.5. 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 behavior to comply with fiscal rules. The report states that advanced analytics is proving a precious tool in improving tax administration effectiveness, meaning that it allows tax administrations to achieve its goals 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.

This OECD report [40] is based upon a survey, which is completed by 16 FTA members, one of which is the Netherlands. In chapter two of the report, six areas are identified that apply analytics: audit case selection, filing and payment compliance, taxpayer's services, debt management, policy evaluation and taxpayer segmentation. 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? If the latter is the case, one expects: fact-based decision making even at the strategic level, analytics that is highly integrated in the business processes, CEO passion about analytics, and broad management commitment.

The OECD report [40] concludes that in the day-to-day work, tax administrations are always 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.

If one looks at the current situation, 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.

2.3.2 Practical experiences in banking and insurance

Banks and insurance companies are in many aspects similar to tax administrations. Banks and insurance companies are mostly large organizations, process large sums of money, have often an extensive IT department, and employ many employees with an accountancy or legal background. For this reason it is interesting to look at these sectors as well.

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, improving customer retention [67]. Simple cluster analysis techniques were used to partition clients into homogeneous 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 [49].

Over time the usage of analytics in banking and insurance has been expanding, resulting in better management of data, more robust data analysis tools, and automation of typical analytical tasks like data pre-processing, model building, and model maintenance. However, the main areas of application 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% [59].

More recently, banking and insurance sectors have been applying 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, according to Acebedo and Durnall [2]. 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 [66]. Insurance companies also use more and more social media like Facebook or Twitter to detect fraud by comparing the client's claims to the information (s)he made publicly available [104].

2.4 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. Firstly — in 2.4.1 — a brief explanation is given of various activities that tax administrations apply in taxpayer supervision when adopting Compliance Risk Management. Subsequently, the technical side of analytics is unraveled in 2.4.2 by providing an overview of modern analytical techniques. Next, in 2.4.3, activities and techniques are mapped onto each other, leading to the first findings. Finally, in 2.4.4, a roadmap for applying analytics in taxpayer supervision is sketched.

2.4.1 Activities in taxpayer supervision

Many western tax authorities have designed their taxpayer supervision according to a so-called Compliance Risk Management approach. The objective of applying Compliance Risk Management is to facilitate the 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 [38]: 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 are 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 risks/taxpayer behavior. Prioritization is needed since resources for treating risks are scarce. In step four, treatment, execution of an agreed supervision strategy 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 2.1 shows the steps and the organizational unit that could perform the related activities. 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 organizational unit within a tax administration. In Table 2.2 we will have a more detailed look at the activities in the various stages.

Table 2.2 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 value of analytics to them. The classification is based upon a) tax literature research (an article mentions the use of analytics for this activity)

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

Table 2.1: Main steps in compliance risk management and typical departments involved

b) international conferences and workshops attended by the author where various tax administrations share best practices and c) desk research for similar sectors, like banking and insurance, that mention the application of certain technique in a very similar problem. The classification in the next column in 'Low', 'Medium', 'High' is based on counting the elements in two columns 'Activities supported by analytics' and 'Activities with no role for analytics'. The classification only could be done roughly because a complete overview of activities is not available and only a limited number of workshops / conferences has been attended by the author. Limitations also arise as some activities require more time than others or are considered more important than others. These two aspects have not been taken into account.

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	
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	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	

Table 2.2: Activities in taxpayer supervision that can be supported with analytics (H = High, M = Medium, L = Low)

Looking at Table 2.2, it seems safe to state that analytics can play a role in all stages of the Compliance Risk Management approach. Analytics may support a substantial number of activities, especially in risk identification, risk analysis, and evaluation. It is also noteworthy to observe that for a substantial number of activities, analytics does not seem to have an added value (see column 'Activities with no role for analytics' in Table 2.2).

According to the experience of the author, cooperation is necessary between analysts, people from the shop floor, process experts, and experts in supervision, to maximally improve the positive effect of analytics. Analysts need to understand the data and processes by talking with domain experts to avoid severe mistakes. Moreover, experts are needed to judge the (initial) analytical results. The intense cooperation between analysts and experts is crucial in the initial, developmental stage.

2.4.2 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 [36]; Cramer, 2003 [29]; Linoff and Berry, 2011 [67]; Larose, 2005 [61]; Liu, 2007 [69]; Leskovec, Rajaraman and Ullman, 2014 [63]). In order not to get lost in details, we have merged some classes of analytical techniques. The merging 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 seen frequently in taxpayer supervision (see Table 2.3):

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 modeling	9. (social) Network analysis
5. Cluster analysis	10. Mining new data sources

Table 2.3: Overview of classes of Analytical techniques

(1) Descriptive statistics. Techniques from descriptive statistics provide fundamental insights by calculating simple summary statistics, visualizing data, or eliminating non-informative data. The latter is often called 'data reduction', or 'feature selection'. Techniques from descriptive statistics 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; see [36, 29]. In taxpayer supervision, descriptive statistics are used for instance, for determining the number of offenders and the amount of lost money of a (compliance) risk.

(2) Experimental design. Surveys and experiments are often needed to gain specialized knowledge. Techniques from experimental design 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, see [36]. In taxpayer supervision, experimental design can help, for instance to design random audit programs that provide more information on risks by sampling the same number of taxpayers. 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 the data supports

an assumption (for instance about the behavior of a group of taxpayers). In taxpayer supervision, this often means checking prior assumptions of experts concerning risks. Typical techniques include statistical tests like the Chi-square test (see also Chapter 5), the F-test (implicitly used in ANOVA), or some non-parametric tests. Introductory textbooks on statistics contain more information on hypothesis testing.

(4) Predictive modeling. With predictive modeling, one tries to predict a characteristic (called ‘target’) of a taxpayer or a tax return statement, with the help of a model. For example, in the 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. A computer algorithm automatically generates a model 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 popular modeling techniques are decision trees, logistic regression, discriminant analysis, k-nearest neighbors, neural networks, support vector machines, and random forests. See for instance [50] for some frequently used techniques.

(5) Cluster analysis. Techniques from 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 , see [29, 69].

(6) Time series analysis. Techniques from time series analysis are applied to find patterns in measurements that are registered periodically. For instance, these techniques can be applied to find a trend or a seasonality impact within monthly sales reported in tax returns. Popular 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, see also chapters 4 and 6. 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 modeling normal behavior (by applying predictive modeling 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 the ratings they give to products. This field has grown substantially with the rise of e-commerce. Novel techniques that can construct recommendation systems are collaborative filtering and matrix factorization [67, 63]. Another popular technique for constructing simple recommendation systems is the A-Priori algorithm [63]. Techniques from recommendation systems are not yet applied much in taxpayer supervision but could help improve taxpayer ser-

vices or gain insight in the combinations of risks.

(9) (social) Network analysis. Techniques from network analysis can be applied to extract information or risks from the (social) network of a taxpayer. In fraud detection these techniques are applied to the network of a fraudster, thus revealing new fraudsters. Network analysis is also applicable for analyzing social media or visualizing complicated legal structures [69, 63].

(10) Mining new data sources. Last decade, the machine learning community put considerable effort into extracting information from data sources that are coming from other sources then relation 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 [69, 63]. 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 pre-processing techniques, like data warehouse technology.

2.4.3 Matching supervision activities and analytical techniques

The classes of analytical techniques from section 2.4.2 can be mapped onto supervision activities of section 2.4.1, resulting in Table 2.4. 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.

Supervision activities and classes of analytical techniques	Descriptive statistics	Experimental design	Hypothesis testing	Predictive modeling	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
Segmentation 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								

Table 2.4: Mapping of (classes of) analytical techniques onto tasks of taxpayer supervision.

Descriptive Statistics is the most applicable class of techniques in taxpayer supervision, according to Table 2.4. The prominent role of descriptive statistics corresponds with practical experience where an initial, simple summary of raw data may already reveal significant insights. Predictive modeling ranks second. Predictive modeling techniques derive their strength in tax administrations from generalizing valuable information, available for a small group, to a much wider group. Think for instance about non-compliance information that is only known for a small number of audited taxpayers. A risk model may, based on this sample, predict the compliance of a much larger group of taxpayers.

2.4.4 A roadmap for analytics in compliance risk management

Davenport and Harris sketch five developmental stages of an analytical business: analytical impaired, localized analytics, analytical aspirations, analytical companies, and analytical competitors [32]. These stages are in no small degree recognizable for tax administrations, although tax administrations lack the competitive framework of businesses.

The first stage, 'analytically impaired', is characterized by businesses making decisions based on intuition only. Data is generally missing or of poor quality and not integrated. Analytical processes are lacking. Stage one is recognizable for some tax administrations 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 [33] a business can overcome stage one by targeting 'low hanging fruit', i.e., identifying small-scale 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 of bottlenecks they experience.

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 lacking, so 'multiple versions of the truth' may exist. In niches, however, isolated analysts might have achieved some excellent, tactical results. In tax administrations, that have many employees, many niches exist and setting up centralized policies takes time. This may be one of the reasons for the frequent occurrence of this stage among tax administrations nowadays. To overcome this stage, a strong effort from senior executives is needed to create a cohesive system of analytical activities [32].

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 [33]. In the United Kingdom, The Netherlands, and some other countries, these transitional activities could be observed in 2016. The third stage is characterized by coordinated analytical objectives, separate analytical processes, analysts in multiple areas of business, early awareness, support of analytical possibilities among executives, and a proliferation of BI-tools. For taxpayer supervision, at least some activities mentioned in Table 2.4 have to be 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.

The fourth stage is characterized by high-quality data, the presence of a Business Information plan, and the incorporation of analytical solutions in some business processes. Full executive support is in place, and change management is applied to build a fact-based culture. Most of the supervision activities of Table 2.4 are supported by analytics. Analytics brings insights to taxpayer supervision, and is structurally embedded in the compliance risk management strategy. In this stage, identification of compliance risks, analysis of trends, and root-cause analyses take place structurally, per segment of taxpayers, enabling a tax administration to match the results with the appropriate treatment.

The fifth stage is characterized by deep strategic insights, fully embedded analytical applications, highly professional analysts, a CEO with a 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 relevant for most tax administrations. The Case Study below presents an initiative from 2014–2017, taken from the Netherlands Tax and Customs Administration.

2.5 Case Study: VAT refund risk model

The Netherlands Tax and Customs Administration (NTCA) receives numerous VAT refunds requests [14]. 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 a VAT refund is 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 modeling techniques. Both the old risk rules and the new risk model take advantage of domain knowledge and available data. The main difference is that with the old risk rules, hypotheses about risky features emerged in the minds of domain experts, and in the new risk model, a computer algorithm generates the hypotheses and subsequently tests them on historical data. The strength of the computer algorithm lies in its power to generate and check a vast amount of hypotheses on the historical data. Although many of the hypotheses generated by the computer algorithm may be of inferior quality compared to the hypotheses brought forward by domain experts, some hypotheses may outperform the old risk rules and only these are kept.

Before the project started, some significant developments had taken place at 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, [110]). The aim of the IA is providing the necessary response to changing taxpayer's expectations and significant technological developments. Within this context, a general trend towards centralization had started. Moreover, an awareness of the potential of analytics has spread among a small group of senior and middle management. The IA made it possible to invest in analytics in a time of budget cuts. Management created a small department ('Data & Analytics', now called 'Datafundamenten & Analytics') that started to realize 'data foundations' and initiated several projects, including the VAT refund project.

The VAT refund project consists of four stages; exploration phase, lab phase, pilot phase, and full implementation phase. A go/no go decision separates each phase. The project finished its full implementation phase successfully in 2017.

The 'exploration phase' aimed at estimating the financial benefits, the impact on processes, and the required changes in ICT. This phase was followed by the 'lab phase', that developed an operating risk model within three months. This first risk model showed promising results on historical data, but was not yet suitable to be applied in operations. In the 'exploration' and in the 'lab phase' approximately three analysts of the NTCA were involved.

After the 'lab phase', the 'pilot phase' followed, aimed at testing the risk model in practice. Two local tax offices were appointed as pilot-location. In the pilot phase, the development team was extended with VAT domain experts. Moreover, a small team of two professional programmers had been formed to streamline the initial code and to make it 'production-ready'. Finally, a pilot-support team of two employees was created to support the two pilot locations on the job floor.

It took three pilots, of three months each, to come to a final risk model delivering expected results. Each pilot refined the model further. For instance, after the first pilot it was noted that the selected tax returns had a high probability of containing an error, but on average a (too) low monetary value. At the end of the 'pilot phase', the regular ICT department became involved to develop a Workflow Management application, that is able to distribute the new risk signals efficiently to the desk auditors who handle the new signals.

As with most analytic projects, some unexpected side results were obtained. For instance, the riskiness of VAT refunds appeared to deviate substantially between the two pilot locations. This suggested shifting part of the workload from one location to the other.

2.6 Conclusions

Analytics seems to be a serious candidate for making taxpayer supervision more effective. Mapping the analytical techniques to the activities in the various stages of a Compliance Risk Management strategy shows the potential for taxpayer supervision in more detail. Nevertheless, analytics cannot support all activities, see Table 2.2. This observation leads to a hypothesis that supervision activities can be split into those that analytics can be improved with analytics and those that cannot. Our inventory Table 2.2 suggests that for taxpayer supervision, about half of the activities can be supported by analytics.

Although the OECD survey [40] 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). The case study of Section 2.5 supports the idea that analytics can improve audit selection. However, there is a risk in paying too much attention to audit selection with analytics. Increasing attention for audit selection may implicitly shift the balance (between prevention and repression) needed in Compliance Risk Management from prevention to repression. This effect may in general 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 canceled by putting more effort 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 taxpayer supervision. The fact that some tax administrations state to apply analytics broadly, can probably be explained since the OECD survey did not make clear to what depth analytics are applied.

Analytics, in our opinion, does not achieve anything fundamentally new when it comes to the type of activities carried out by a tax administration. However, analytics could improve the foundation for a Compliance Risk Management strategy, leading to more rational decisions made by the management of a tax administration. Analytics, from that perspective, complements Compliance Risk Management. 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 behavior to comply with the rules. Before really confirming that analytics is more efficient and effective for taxpayer supervision, more proof is needed, and therefore, tax administrations are urged to measure the impact of their (analytical) activities.

2.7 Discussion

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 the right conclusions from the output of the techniques and to prevent automatic decision-making with far-reaching consequences for taxpayers. 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 fiscal correction when studied by a domain expert. Therefore, it is essential to realize that analytics must support human experts and not vice versa.

An obvious limitation of analytical techniques is that one cannot get insights out of data that are not present in the data. For instance, insights cannot be extracted from data for new risks (e.g. risks related to new legislation). Moreover, available data may contain insufficient information to be 100% confident on a risk. More likely, the data contains clues, leading to an increased risk level, without providing certainty.

Privacy issues (as well as ethical issues) are of primal concern when applying analytics. At present, research is done to analyze data while preserving the privacy of individuals. This field is known as 'privacy preserving data mining'. Although some algorithms have been proved to preserve privacy, care should still be taken to manage the whole process adequately. More on privacy issues and analytics can be found in Haddadi et al [46].