SOCIAL MECHANISMS OF TAX BEHAVIOUR

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To Ana

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Abstract

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Social Mechanisms of Tax Behaviour

The main goal of this thesis is to provide a sociologically informed analysis of tax avoidance and tax evasion in contemporary Mexico and Sweden, focusing particular attention on the explanatory role of social networks, social interactions, and positive feedback mechanisms.

Two major data sources are used: (1) A panel dataset that includes all persons, 16 years or older, who resided in Stockholm County during at least one of the years 1990 to 2003 (N=1,967,993). The dataset includes detailed information on the socio-demographic characteristics, kinship networks, and criminal offenses of these individuals; (2) A random sample of 36,949 firms that appeared in the Mexican Federal Register of Taxpayers for the year 2002. The records of the Mexican Federal Administrative Fiscal Tribunal provided data on all types of tax claims appealed before them during the 2002-2008 period.

A variety of approaches and techniques are used such as agent-based simulation models, discrete time event history models, random effect logit models, and hierarchical linear models. These models are used to test different hypotheses related to the role of social networks, social interactions, and positive feedback mechanisms in explaining tax behaviour.

There are five major empirical findings. (1) Networks seem to matter for individuals' tax behaviour because exposure to tax crimes of family members appears to increase a person's likelihood of committing a tax crime. (2) Positive feedback mechanisms appear relevant because if a person commits a tax crime, it seems to increase the likelihood that the person will commit more tax crimes in the future. (3) Positive feedback mechanisms are also important for explaining corporate tax behaviour because a firm that has engaged in legal tax avoidance in the past appears to be more likely to engage in tax avoidance in the future. (4) Network effects are important in the corporate world because exposure to the tax avoidance of other firms increase the propensity of a firm to engage in tax avoidance. (5) Substitution effects between tax evasion and tax avoidance are likely to exist because when tax evasion becomes more prevalent in a firm's environment, their likelihood of engaging in legal tax avoidance is lowered.

The results underscore the importance of a sociological perspective on tax behaviour that takes into account social interactions and positive feedback mechanisms. In order to understand microscopic as well as macroscopic tax evasion patterns, the results presented in this thesis suggest that much more attention must be given to mechanisms through which taxation crimes breed more taxation crimes.

Word count: 44, 823

Introductory

Preface and introduction

Taxes as we know them today became important long before the arrival of tax states. Although most modern forms of tax collection emerged in the twentieth century, tax collection can be traced back to the primary communities of Mesopotamia and classical antiquity where conquering rulers imposed tributes and gifts on society at large. Taxation issues have had important and interesting social dimensions throughout history. In Babylonia's old cities, for example, taxing the property of citizens was prohibited because it was considered to be degrading, but taxing non-citizens' income was seen as fair.[1] Social interactions also seem to have played an important role for understanding taxation issues throughout history. Persons in Athens, for example, had the right to accuse those who did not pay for public goods, and whenever the accusation was proved real and the accused person still refused to pay, she was forced to exchange the property involved in the dispute with the accuser.[2]

Despite the fact that taxes and tax behaviour are socially and economically important and have interesting and noteworthy social dimensions, sociologists have not paid much attention to taxation issues. Taxation research instead is a field dominated by economists. Although the economic approach to tax behaviour has many strong sides, from a sociological point of view it nevertheless appears wanting because many potentially important explanatory mechanisms are ignored.

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[1] See Austin and Vidal-Naquet (1977). In order to get a broader sense of how tax collection has brought about different social structures since ancient societies see Hudson (2000).

[2] See Andreades and Brown (1933) cited in Hudson (2000: 13)

The analytical sociology approach adopted in this thesis seeks to identify various social mechanisms likely to explain tax behaviour. A "social mechanism" can be defined as "a constellation of entities and activities that is organized in such a way that it regularly brings about a particular type of outcome" (Hedström, 2005: 145). It provides an explanatory account for individual behaviour, i.e., in the context of this thesis, the mechanisms of interest show why taxpayers' do what they do. In addition to understanding individual behaviour, we want to know what collective outcomes individuals are likely to bring about when they act as they do. As often is the case (cf. Merton, 1936; Boudon 1982), the sociologically most interesting collective outcomes are entirely unanticipated by the individuals themselves. Accordingly, Backhaus (2002) and other authors (Campbell 1993; Moore 2003; Marques 2004) have argued that sociologists interested in taxation issues should pay particular attention to their unintended social consequences; for example, how well-informed and well-intended fiscal reforms may "pervert" the behaviour of individuals in various unanticipated ways.

The main goal of this dissertation is to provide a theoretically informed empirical analysis of tax compliance and tax evasion. Some chapters focus on individual tax behaviour while others analyse corporate behaviour; some chapters analyse tax evasion while others focus on tax avoidance;[3] and some chapters focus on Sweden while others are concerned with Mexico. Underlying them all, however, is a concern with the explanatory role of social networks, social interactions, and positive feedback mechanisms.

[3] Tax *avoidance* refers to legal actions aimed at reducing one's taxes, while tax *evasion* refers to illegal actions aimed at reducing one's taxes.

I start Chapter 1 with describing the core of the economic approach to tax behaviour and I identify what I consider to be some of its main weaknesses. Thereafter, I present the core ideas of the generic analytical sociology approach, and in much more detail, I discuss what an analytical approach to the study of tax behaviour implies. In doing this, I identify and describe the "logic" of a range of social mechanisms likely to be of crucial importance for explaining tax behaviour. Chapter 1 ends with presenting the results of an agent-based simulation model linking micro mechanisms to macro outcomes. The agent-based model formalizes some of the social mechanisms discussed earlier in the chapter, and the analysis shows that social-interactions and social networks in and of themselves can be of crucial importance for patterns of tax evasion.

Chapter 2 focuses on tax-related crimes, i.e., tax evasion and bookkeeping crimes. It examines the extent to which such crimes "run in the family". This chapter and the next use data from a unique longitudinal database on the adult population of Stockholm County during the years 1990 to 2003. It contains detailed socio-demographic information on all individuals as well as data on the crimes that they have committed or being suspected of having committed. In addition it contains information that makes it possible to map complete kin networks and the chapter examines whether the person's likelihood of committing a tax-related crime is influenced by close and distant kin committing such a crime (controlling for other relevant factors).

Chapter 3 focuses on positive-feedback processes in criminal behaviour. An important finding in Chapter 2 as well as in much of the criminological literature is that people who commit criminal offenses at one point in time, are much more likely than non-offenders to commit crimes at later points in time as well. In this chapter I discuss various mechanisms that could produce such path dependencies, and formulate various empirically testable hypotheses. The fact that past and current crimes are related to one another does not necessarily mean that past crimes causes current crimes, however. It could also be due to unobserved heterogeneity. For this reason, when testing these hypotheses I estimate panel models that control for unobserved heterogeneity.

An important shortcoming of the existing tax literature is that it almost exclusively focuses on tax evasion at the expense of legal tax avoidance. This is an unfortunate omission because the causal path into tax evasion usually includes tax avoidance. A second shortcoming of the literature is that it pays only limited attention to corporate tax behaviour. Directly applying models for individuals' tax behaviour to corporations can be highly misleading because models of individual tax behaviour assume that the decision-makers are persons, not organizations; thereby, the principal-agent problem and other organizational dynamics are left out of the analysis.

Chapter 4 responds to this gap in the literature. It shows that legal tax avoidance is prevalent in Mexico, and that it has considerable fiscal consequences. Based on data consisting of a random sample of all firms that appeared in the Mexican Federal Register of Taxpayers for the year 2002, a discrete time event history model is used to test three hypotheses. These hypotheses relate tax-avoidance behaviour to (1) the resources of the firms; (2) positive feedback; and (3) social interactions. The results of the statistical analysis suggest that there exists important social interaction effects and that a learning-by-doing process may be important for explaining tax-behaviour dynamics. Therefore, the empirical evidence presented in this chapter underscores the importance of better understanding the legal tax avoidance behaviour of corporations.

Using the same data as in Chapter 4, Chapter 5 focuses on one particular type of tax evasion: a firm's decision to leave the legal arena. First, a multilevel model is used to analyse how the variation in this type of fiscal evasion is related to the prevalence of tax evasion in their environment and to their own tax avoidance practices. Second, a discrete time event history model is estimated which further underscores the importance of social interactions. Both types of analyses show that firms who lose a tax trial are markedly more likely to exit the legal arena than are those who won a trial.

The thesis ends with a brief summary and discussion of the results presented in the previous chapters. In this final section I summarize the entire thesis, draw more general conclusions based upon the results presented in the various chapters, and discuss important research questions and policy implications brought to the foreground by the results reported in the thesis.

Chapter 1. Social Aspects of Tax Behaviour: An Analytical Approach

1.1. Introduction

Taxation is of considerable social and economic importance. Through taxation, the most important public goods in society are financed, and taxation is a crucial tool for redistribution of resources in society. In addition, taxes influence individuals' incentives for engaging in different kinds of activities, and the progressivity of the tax system has important institutional and social dimensions (see e.g., Atkinson and Bourguignon 2000; Masclet, Noussair, Tucker, and Villeval 2003; Salverda, Nolan, and Smeeding 2009).[4]

Tax evasion and tax avoidance also are of considerable importance and are common all over the world. Even in the United States, which is considered to be a high-compliance country, tax evasion and tax avoidance are common. According to estimates of Slemrod (2007), the US government failed to collect almost one tax dollar out of seven in 2001 (p. 28).

Despite the fact that taxes, tax evasion, and tax avoidance are socially and economically important and that they have interesting and noteworthy

[4] See, in particular, the literature on redistributive justice and on fiscal equity. For an overview of this literature, see Piketty (1999a); Piketty (1999b); Piketty (2005); Alvaredo and Saez (2009); and Atkinson et al. (2011).

social dimensions, sociologists have not paid much attention to taxation issues. During the years 1900 to 2011, 10,780 articles were published in the two flagship journals of the discipline, *American Journal of Sociology* and *American Sociological Review*. Of these, only 36 made any reference to tax, taxation, or taxes in their abstracts, and none of them had anything to do with tax evasion or tax avoidance (see Table 1.1).

Table 1.1. Number of articles published in *American Journal of Sociology* and *American Sociological Review*, during the years 1900 to May 2011 dealing with "tax, taxation, taxes", "economy, economic", "income", and other "fiscal" matters as identified by the contents of their abstracts published in the Web of Science.

	SEARCH WORDS:			
YEARS:	Tax, taxation taxes	Economy economic	Income	Fiscal
1900-20	0	0	0	0
1921-30	4	27	4	1
1931-40	7	77	21	0
1941-50	0	69	15	0
1951-60	0	52	27	0
1961-70	1	100	36	0
1971-80	1	142	87	4
1981-90	7	118	66	6
1991-95	5	92	33	4
1996-00	2	89	40	2
2001-05	6	81	27	0
2006-11	3	66	17	5
Total:	36	913	373	22

In fact, in only four articles (Allen and Campbell 1994; Kiser and Schneider 1994; Morgan and Prasad 2009; Wilson 2011) was some aspect of the tax system the "dependent variable" of the analysis.[5] In most of the other articles, it was used as an unexplained independent variable in analyses seeking to explain outcomes such as residential mobility (e.g., Logan and Schneider 1984) and the extent of income inequality in different nations (e.g., Lee 2005).

Research on tax systems and tax behaviour instead has come to be dominated by economists. The economic approach to tax behaviour is a strong paradigm due to its clarity, rigor, and precision, but from a sociological point of view it nevertheless appears wanting because many potentially important explanatory mechanisms are ignored. The main goal of this chapter is to describe in some detail the logic of various social mechanisms that are likely to be important for explaining tax behaviour, some of which will be empirically tested in later chapters.

The chapter is organized as follows. I start with describing the core of the economic approach to tax behaviour, and this leads over to a discussion of some of the most influential recent work on tax evasion. Thereafter, I present the analytical approach to sociological theory and research. First I present the core ideas of the generic analytical approach, and then, in much more detail, I discuss what an analytical approach to the study of tax behaviour implies, and I identify a range of social mechanisms likely to be of crucial importance for explaining tax evasion and tax avoidance.

A basic tenet of the analytical approach is that social interactions and social networks matter a lot for the collective outcomes that individuals

[5] In less central journals of the discipline some interesting sociological work can be found, however, such as that of Becker and Mehlkop (2006).

bring about. To demonstrate more precisely the potential relevance of this approach for explaining variations in tax behaviour, the chapter ends with presenting the results of an agent-based simulation model that formalizes some of the mechanisms likely to be of importance. The analysis shows that social-interactions and social networks in and of themselves can be of crucial importance for explaining aspects of tax evasion in society at large.

1.2. Existing theories of tax behaviour

1.2.1. The economic approach

Since the seminal work of Becker (1968), the economic analysis of criminal behaviour has received considerable attention. Becker's approach provided a rigorous explanation of criminal behaviour in terms of the likely costs and benefits of engaging in a criminal activity. Becker argued that "some persons become 'criminals' [...] not because their basic motivation differs from that of other persons, but because their benefits and costs differ" (1968: 176).

Allingham and Sandmo (1972) further developed Becker's model and applied it to tax behaviour, and their model is generally seen as an ideal type of the traditional economic approach to taxation. Their model assumes that the decision whether or not to evade taxes is like any other decision under risk. The decision-theoretic core of their model can be described with reference to the decision tree in Figure 1.1, where **E** stands for evading taxes and **C** stands for compliance with the tax law.

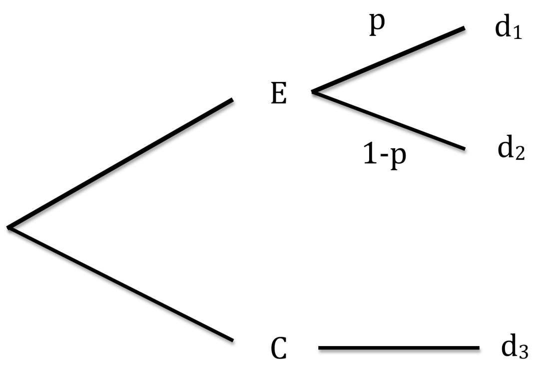

Figure 1.1. Decision tree illustrating the decision-theoretic core of the Allingham-Sandmo model.

The individual is faced with a decision of whether or not to evade taxes. If she decides to comply with the tax legislation and not to evade, she knows with certainty that the outcome will be d_3. If she were to evade taxes, two possible outcomes exist: (1) That the taxation authority detects her tax evasion and then the outcome will be d_1, and (2) that the tax evasion is not detected and then the outcome will be d_2. The letter p represents the probability of being detected, and the rank-order of the three outcomes typically are as follows: $d_2 > d_3 > d_1$. That is to say, individuals contemplate tax evasion because successful evasion (d_2) is more advantageous than complying with the law and paying one's taxes (d_3), and typically it is better to pay one's taxes (d_3) than to evade and being caught (d_1) because the penalty for being caught usually is such that $d_1 < d_3$.

According to Allingham and Sandmo and other analysts working within this tradition, explanations of tax evasion should assume that individuals are rational actors and the explanation should refer to the expected costs and benefits of the evasion. As is well known from the decision-theoretic literature, a rational actor should evade taxes if $(p \times d_1 + (1-p) \times d_2) > d_3$, i.e., if the expected value of evading is greater than the expected value of not evading. Consequently, when seeking to explain the variation in tax evasion between individuals, groups, or nations, those working within this tradition have focused their attention on variations in detection probabilities (p) and variations in the penalties for tax evasion (the higher the penalty is, the lower d_1 will be in relation to d_3).

Although the Allingham-Sandmo model has been very successful in academic terms, it has not been as successful in empirical terms. As noted by Andreoni et al. (1998) in their detailed review of the tax compliance literature:

> The most significant discrepancy that has been documented between the standard economic model of compliance and real-world compliance behaviour is that the theoretical model greatly over-predicts noncompliance. (p. 855)

That is to say, if individuals acted as assumed in the Allingham-Sandmo model, tax evasion would be far more common than it actually is. The detection probabilities and to some extent also the penalties for tax evasion typically are so low that one would expect most individuals to evade taxes if they acted as assumed in the Allingham-Sandmo model. [6] That is not the case, however, and this suggests that causally important elements are left out of the standard economic model.

It should also be mentioned that there exist a small but vital tradition of taxation-related research within political science (see Gould and Baker 2002 for an overview of parts of this literature). The majority of the work in this tradition follows a rather different path than the one adopted here, however. In terms of the Coleman graph of Figure 1.2, most of this research is concerned with macro-macro relationships, and tend not to be concerned with tax evasion. Rather, most of the empirical research produced within this tradition is concerned with comparing nations and investigating aggregate relationships between various properties of the electorate, the political institutions and the political environment, on the one hand, and properties of the taxation system such as the amount of tax revenues being collected and the progressivity of the tax system, on the other. For example, Swank and Steinmo (2002) estimate cross-sectional time-series models for 14 countries to examine how observed changes in the tax structure of these nations during the years 1981 to 1995 relate to indicators on the extent of international trade and capital mobility as well as various domestic policy-related measures.

[6] In the case of United States, Alm et al. (1992: 22) presented empirical results suggesting that "the percentage of individual income tax returns that are subject to a thorough tax audit is quite small [...] less than 1 per cent in recent years". Thus it is highly unlikely that a person will be caught if he/she evades taxes, and if we assume that people act rationally in a purely self-interested manner, we would expect a much lower tax compliance rate than observed in reality. It should be noted, though, that the opportunity side also matters. That is, even if detection probabilities were zero, many employees could not evade taxes because their employers report all of their incomes to the tax authorities.

Given the influence of economic theory on political science, rational-choice accounts of course sometimes are used to make sense of the empirical findings (e.g., Levi 1988, Meltzer and Richard 1981), but the actor-based accounts usually are used for purely interpretative or sense-making purposes, i.e., empirical data on the behaviour of single individuals rarely is used. Some of the modelling work is highly interesting, however, but since they are not concerned with tax evasion they tend to be of limited relevance for this thesis.[7]

1.2.2. From atomistic to social behaviour

Although the core of the original economic model focuses exclusively on audit rates, probabilities of being caught, and penalties, economists working in this tradition have gradually expanded the approach to also consider various social factors, most importantly social stigma and feelings of guilt.[8] Schwartz and Orleans (1967) was an important source of inspiration for this development. They presented important evidence suggesting that social controls other than mere legal sanctions also are important for explaining tax evasion. Their evidence derived from an experiment conducted by the Internal Revenue Service in United States that found that "guilt feelings" (self-imposed punishment) played a more important role for individuals than did legal sanctions (state-imposed punishment) (p. 300). Supporting this socially oriented approach, Alm and

[7] Steinmo currently is directing a large-scale project that seeks to combine the type of macro-level institutional information that typically is used in this research tradition with micro-level data derived from identical tax-related experiments conducted in a range of different nations. This is likely to produce a wealth of interesting results but nothing has been published yet.

[8] See Andreoni et al. (1998) for a more exhaustive review of the literature on tax compliance behaviour. For a more critical revision of the traditional economic model on tax evasion see also, Graetz and Wilde (1985).

Mckee (1992), Alm and Schulze (1992), and Alm et al. (1995) have presented further evidence suggesting that social norms are highly important for explaining tax behaviour.

In this new line of behavioural research, social norms are given a prominent explanatory role and the strength of the relevant norms are seen as being a function of factors such as fiscal transparency (Nerre 2008), the perceived fairness of the tax system (Carroll 1992; Lempert 1992; Smith 1992; Lederman 2003a),[9] trust in public institutions (Torgler 2003), and beliefs about the extent to which the rule of law governs (Van Vugt et al, 2000; Moore 2003; Torgler and Schneider 2009).[10] In addition, the individual's own socioeconomic status and income level have been shown to influence the strength of this norm (Becker, Buchner, and Sleeking 1987; Alm and Torgler 2006).[11] Factors like these thus constitute core elements for explaining individual's willingness to pay taxes.[12]

Feld and Frey (2007) further argued that social ties and loyalties are highly important elements in these processes. On-going social interactions develop

[9] It is not always the case, however, that the fairness of the tax system deters tax evasion. See the work of Forest and Sheffrin (2002) and Kim (2002) for a different view on this.
[10] See also Vogel (1974); Myles and Naylor (1996); Kahan (1997); Cooter (2000); Cooter and Eisenberg (2000); Torgler (2002); Davis et al. (2003); Kahan (2005); Frey and Torgler (2007); Fortin et al. (2007); Maciejovsky et al. (2012).
[11] Regarding the specific effects of socioeconomic status, Alm and Torgler (2006) present empirical evidence on how in Spain and the United States the lowest economic class holds the highest tax morale.
[12] Based on data from a nationwide sample from 1969 that contained 1,796 Swedish taxpayers, Vogel (1974) developed a taxpayers' typology upon which objective factors such as the quality of public expenditure, i.e. what people receive in return for their taxes, social and political orientation (mainly party affiliation) and real access to opportunities to reduce tax liabilities, have an impact on people's attitudes towards tax evasion. For behavioural experiments supporting how social norms and social interactions influence individual's decision to evade, see Spicer and Lundstedt (1976); Friedland, Maital, and Rutenberg (1978); Spicer and Becker (1980); Spicer and Thomas (1982); Spicer and Hero (1985); Falk and Fischbacher (2002); Coleman (2007); Fortin, Lacroix, and Villeval (2007).

a kind of implicit “psychological contract” through which others’ tax ethics reinforces an individual’s willingness to pay taxes. Tax behaviour and social interactions have also been analysed from a collective-action perspective (Greenberg 1984; Cowell 1990; Frey and Holler 1998; Van Vugt, Snyder, Tyler, and Biel 2000). For instance, in opposition to Becker’s individualistic and static decision-theoretic approach, Cowell (1990) emphasizes the importance of strategic interdependencies:

> [The] individualistic approach is unsatisfactory in several respects. It neglects the potential for strategic behaviour by individual citizens, groups of citizens, and the authorities; it overlooks the possibility that participation in evasion may be driven by perceived injustices and inequalities in the tax system; and it ignores the influence of the prevailing social climate upon each person’s willingness to take a chance and break the law. No tax evader is an island, entire of itself. (p. 101)

According to Cowell, taxpayers might be more or less rational but, at least, they are strategic, and taxpayers' actions are in part based on how they think others will act. Cowell uses an n-person assurance game to analyse the decisions whether to evade taxes or not. The probability of evading increases if more people evade, but at the same time the utility of evading decreases because of a suboptimal production of public goods (pp. 111-12). The intersection of these two factors leads to equilibrium where the probability of evading and not evading are equal to one another. The equilibrium is highly unstable, however. If a small perpetuation occurs that leads to more evaders than the equilibrium level, a bandwagon effect will come into play and evading becomes the optimal choice; thus suggesting the possibility of an "evasion epidemic".[13]

Fehr and Gintis' work (2007) on social reciprocity has similar implications for our understanding of tax behaviour in that it emphasizes how important the behaviour of others is for explaining why individuals do what they do. They refer to a range of experimental studies that suggest that most individuals are neither egoist nor altruists, but *conditional altruists* who contribute to a public good if others are doing the same. While conditional altruists will pay their taxes as long as others do the same, they will evade taxes if they believe others are doing so. Hence, a minority of tax evaders or avoiders can change the tax behaviour of the majority through some sort of social contagion process. That is to say, the tax behaviour of some influences the beliefs and behaviour of others, which in turn influences the beliefs and behaviours of yet others, and so on.

Although the traditional economic crime model is limited because of its under-socialized conception of the actor, I do not want to downplay the importance of the mechanisms that are at the heart of the approach. It clearly is the case that detection probabilities and the severity of punishments play an important role in explaining tax behaviour (Slemrod 2007), but existing empirical research does not suggest that they play the all-important role that the standard economic model attributes to them (see also Alm, Jackson, and Mckee 1992). My reading of the literature suggests that tax behaviour needs to be analysed within a broader analytical framework that systematically takes into account different social

[13] Tipping behaviour is also shown in the computational experiment of Davis et al. (2003).

mechanisms that link the taxation behaviour of different individuals to one another. Therefore, in the next section I will introduce the analytical sociology framework that I use for theoretical guidance.

1.3. The analytical sociology approach

In addition to trying to better understand the social aspects of tax behaviour, I hope this chapter will contribute to the rapidly expanding theoretical toolbox of analytical sociology (see Hedström 2005; Hedström and Bearman 2009). The analytical approach is founded on the premise that proper explanations detail the social mechanisms that generate the social outcomes to be explained (see Elster 1989a; 1989b). The main reason for emphasizing so strongly the importance of clearly specified mechanisms is that we are likely to arrive at better answers to the question of why we observe the social phenomena we observe if we specify the individual-level mechanisms likely to have brought them about. Furthermore, and as a side effect, detailing the mechanisms at work is likely to lead to more useful theories in that knowing how things are brought about will help us if we want to alter the process in a more desirable direction. In this section I will present the core ideas of analytical sociology and I will show what these ideas imply for the explanation of tax behaviour.

As argued by Manzo (2010:140), analytical sociology “provides a ‘syntax’ of explanation; that is to say, a set of rules on how to build and empirically test hypotheses about mechanisms underlying regularities in social life” (see also Hedström 2005; Hedström and Bearman 2009). Analytical sociology is founded on the premise that proper explanations detail the social mechanisms that generate the social outcomes to be explained. Macro-level outcomes are not explained merely by relating them to other macro-level properties, but by detailing in clear and precise ways the social mechanisms and social processes through which they were formed. The approach thus is closely related to the methodological prescriptions of Coleman (1986; 1990) as they were summarized in his famous micro-macro graph (see Figure 1.2).[14]

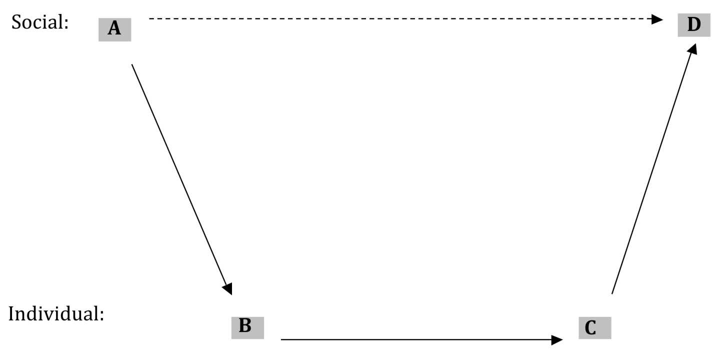

Figure 1.2 Coleman's micro-macro links (Coleman 1986).

Coleman argued that "the characteristic problem in sociology is that of accounting for some aspect of the functioning of a social system. Put in causal diagram form, it can be seen as the effect of one macro-level variable on another" (1986: 1321). In Figure 1.2, this is illustrated by the dashed arrow from macro-property A to macro-property D. In order to explain why and how A and D are related to one another, Coleman argued for the

[14] The realist orientation of analytical sociology results in some important differences between the two approaches, however. Most importantly, although analytical sociology typically assumes that individuals are intentional beings, many analytical sociologists are reluctant to embrace the simplified and heroic actor assumptions underlying Coleman's type of rational-choice approach; see Hedström (2005) and Boudon (1991).

necessity of explicating the links between micro and macro as indicated by the solid arrows in the graph. That is to say, in order to explain the observed macro-level regularity between A and D, first one has to show how macro property A influences individuals' assessments of different action alternatives (B); how these assessments influence their actions (C); and how these actions generate the macro-level property which is to be explained (D).

The crucial causal part of the analysis thus concerns the A->B->C link in Figure 1.2, i.e., how a macro-level property influences individuals' assessments of different action alternatives, and how these assessments in turn influence their actions. In order to explicate the logic of and importance of action assessments, I take my point of departure in so-called DBO theory, i.e., in an action theory where desires, beliefs, and opportunities are the primary theoretical terms upon which the analysis of action and interaction is based (Hedström 2005).

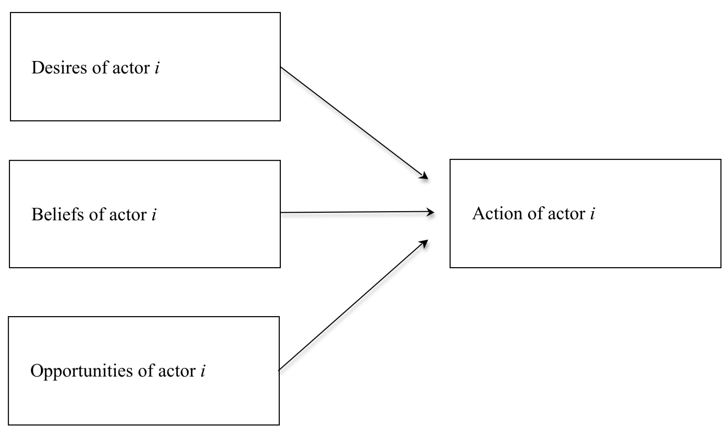

Figure 1.3 Core components of DBO theory.

Space does not allow for a detailed presentation of DBO theory, but desires and beliefs are seen as having a motivational force that allows us to understand and, in this respect, explain the actions. Therefore, the cause of an action can be understood as a constellation of desires, beliefs, and opportunities in the light of which the action appears reasonable. That is to say, an individual will carry out an action if she has an opportunity to do so and believes that it will bring about a desired outcome. Similarly, if a macro-level property or an action of another individual influences an individual's actions, it must do so by influencing her desires, beliefs, or opportunities (see Hedström 2005 for a detailed discussion of this approach).

In addition to underlining the importance of making explicit the mechanisms linking micro behaviour and macro properties to one another, the analytical approach emphasizes the importance of taking time, change, and social processes seriously. Actions not only are influenced by the macro-level structures within which they take place, they also shape and transform these structures. Since the actions of some change the macro-level environments of others, a feedback loop exists between actions and macro-level structures that tend to be of crucial importance for explaining macro-level change. For this reason, although providing micro foundations is necessary, it is not sufficient; we must also explain why, acting as they do, individuals generate the macro outcomes they do. As Granovetter (1978: 1421) explains "knowing the norms, preferences, motives, and beliefs of individuals can, in most cases, only provide a necessary but not a sufficient condition for the explanation of collective outcomes; in addition, one needs a model of how these individual preferences interact and aggregate". Schelling's (1978) analyses of micro motives and macro dynamics remain the key illustration of this point.

1.3.1. Towards an analytical sociology of tax behaviour

The explanatory "syntax" of analytical sociology means that a theoretical explanation needs to accomplish two separate tasks: (1) it needs to identify social mechanisms likely to be at work, and (2) it needs to establish that the macro-level outcome to be explained could follow if these mechanisms were in operation.

Different authors use "micro" and "macro" in different ways (see Cherkaoui 2001 for a brief overview). Here these concepts are used to distinguish between attributes and behaviour of actors (micro), on the one hand, and attributes and dynamics of institutions and social aggregates (macro), on the other hand. Examples of macro phenomena of importance in this context include the prevalence of tax evasion and tax avoidance in different groups or in society at large, properties of the networks in which individuals are embedded, properties of the tax system such as taxation levels and progressivity of the tax code, and the legitimacy of the government which the taxes are to finance.

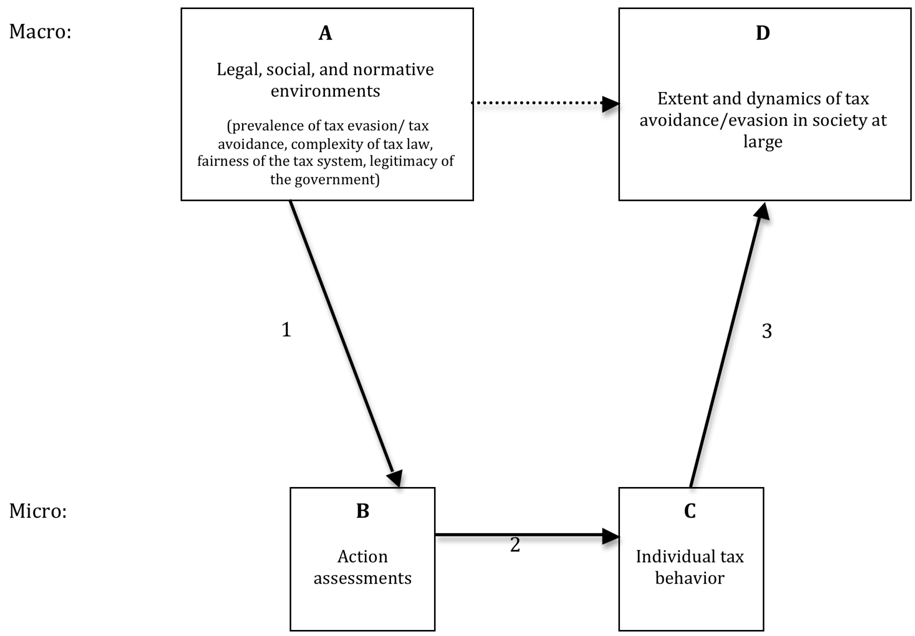

Figure 1.4. Core micro-macro links needed to explain tax behaviour.

As can be seen in Figure 1.4, the first two links indicate how various aspects of the environments (A) in which individuals are embedded influence their action assessments (B), i.e., their relevant beliefs, desires, and opportunities, and how these action assessments, in turn, influence the individual's tax behaviour (C). The focus of the third arrow is on the link between micro and macro and details how the tax behaviours of a large number of individuals bring about different levels and patterns of tax evasion and tax avoidance in society at large (D).

Thus, as applied to the case of tax behaviour, the analytical approach implies that the explanatory focus should be on macro-level properties such as the extent of tax evasion in different groups or in different societies. In order to explain such variations, it is not sufficient to merely relate them to other macro-level properties describing the groups or societies in question, however. Explicit links between micro and macro must be detailed.

1.3.2. Beliefs preceding the other action assessments

As explained above, beliefs, opportunities and desires jointly are seen as the relevant action-assessment dimensions needed for explaining why actors act the way they do. In certain situations, however, beliefs can be said to be more crucial because they causally precede and influence desires and perceived opportunities. This is the case with tax behaviour, and thus while I take my point of departure in the DBO-model, the model I use deviate slightly from the standard model.

When it comes to explaining why an individual evades taxes, it is not the actual opportunities that are important but rather the individual's beliefs or knowledge about the opportunities. Beliefs also are important because irrespectively of what others do, an individual's beliefs about what others do will influence his/her perceptions of normativity and the normative pressures felt by the individual. In such cases, it is not the true state of the world that matters but the individual's beliefs about the world. This insight was emphasized already in the so-called Thomas theorem: 'If men define situations as real, they are real in their consequences' (in Thomas and Thomas, 1928: 571-572). This assumption also was at the heart of Merton's (1968b) notion of the self-fulfilling prophecy. As Merton showed, because of the mechanism expressed in the Thomas Theorem, even an initially false belief can set in motion a process that eventually makes the false belief come true. Figure 1.5 shows with more clarity the relationships that are assumed to exist.

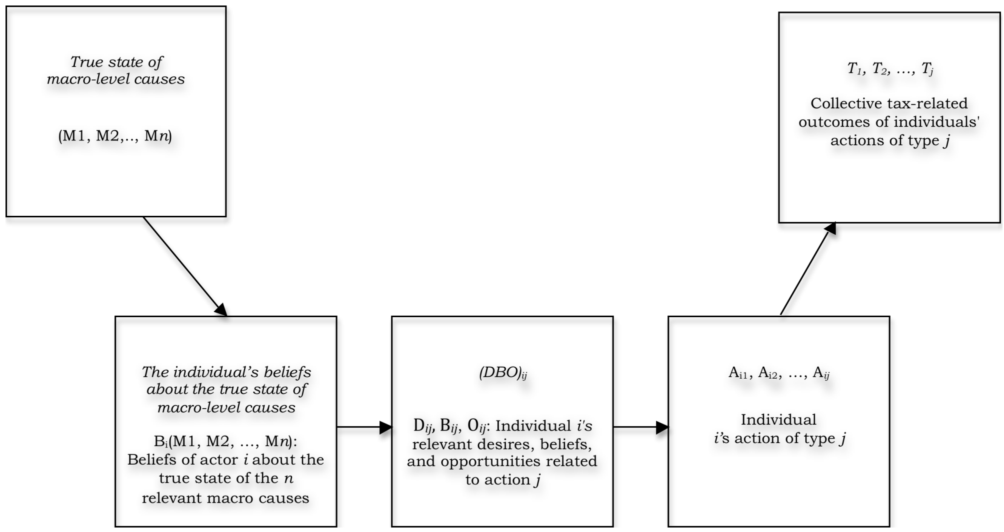

Figure 1.5. Modified DBO-model emphasizing how beliefs causally precede and influence desires and perceived action opportunities.

In the figure above, M_n stands for the true state of the relevant macro cause n; B_{ij}, O_{ij}, *and* D_{ij} refer to individual *i's* relevant beliefs, opportunities, and desires related to action of type j; A_{ij} indicates individual i's action of type j; and finally Tj refers to the collective outcomes of individuals' actions of type j.[15]

In order to systematically specify the various types of social mechanisms likely to be relevant for explaining tax behaviour, Figure 1.6 summarizes

[15] The reason for making this distinction between j and n is that I only focus on a small subset of actions (j=2, i.e., evasion and avoidance) while the full set of n macro causes is much larger and different from the two that I consider here.

the relevant information presented earlier in this chapter using the categories of the Coleman graph.

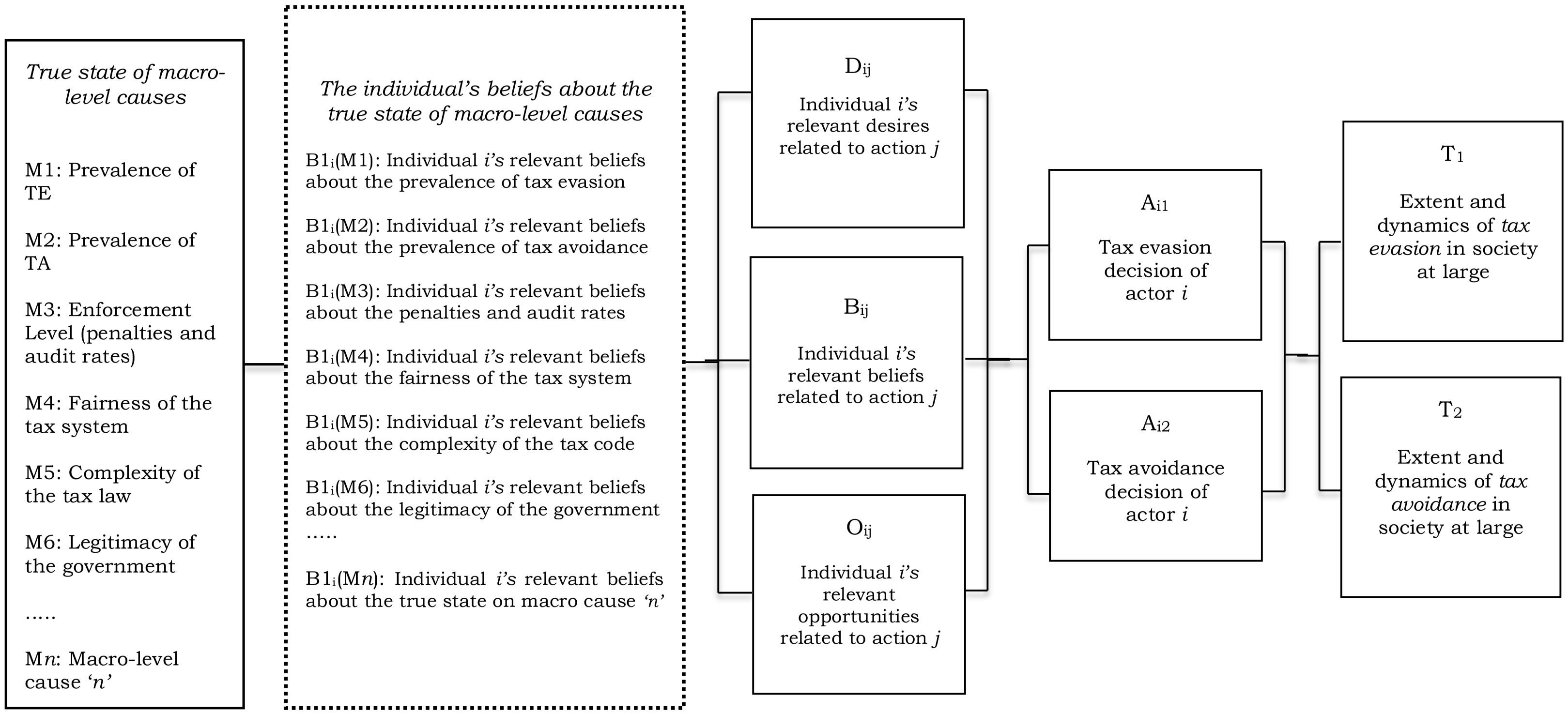

Figure 1.6. Scheme for entities typically relevant for an analytically oriented explanation of tax behaviour

Figure 1.6 highlights the special role played by beliefs in that they causally precede and thereby influence an individual's desires and perceived opportunities to reduce his/her tax liabilities. In other words, when explaining why an individual pays taxes or not, it is not the actual opportunities to reduce tax liabilities that are important but the individual's beliefs or knowledge about existing opportunities. Similarly, irrespectively of the extent of tax evasion in society at large or in the relevant reference group, if an individual believes that it is widespread, it is likely to influence the normative pressure felt by the individual and the individual's likelihood of evading. For this reason, the self-fulfilling prophecy also can be important for explaining the extent of tax evasion. If individuals incorrectly believe that tax evasion is widespread, perhaps because of biased news reporting, the normative pressure against tax evasion is likely to be lower than what it otherwise would have been. This may tip the balance for some and make them evade taxes. If this becomes known to yet others, this may tip their decision calculus as well, and if this process continues, we may eventually end up in a situation where the initially false belief becomes true.

The central role of beliefs is not limited to beliefs about the tax behaviour of others, of course. Beliefs about the extent of corruption and biased spending priorities, for example, is likely to operate in a similar manner and influence the tax behaviour of the individuals.

Using the categories in Figure 1.6, Table 1.2 identifies twelve types of social mechanisms likely to be relevant for explaining the extent of tax evasion and tax avoidance in different groups or societies. Mechanisms 1-2 explicate pure endogenous feedback-mechanisms; mechanisms 3-4 link tax avoidance and tax evasion to one another; and mechanisms 5-12 link properties of the tax system and the government to individuals' tax behaviour.[16]

In order to illustrate how Table 1.2 should be read, I will only explicate in some detail mechanisms 1 to 3, on the one hand, and mechanism 5 and 6, on the other. The text in the table should provide sufficient information for the reader who is interested in some of the other mechanisms.

Table 1.2. Types of social mechanisms likely to be relevant for explaining the prevalence of tax evasion and tax avoidance in society at large.

TYPE OF MECHANISM:	DESCRIPTION:	ID:
$M1 \Rightarrow B_i\,(M1) \Rightarrow (DBO)_{ij} \Rightarrow A_{i1} \Rightarrow T_1$	An increase in the prevalence of T_1 (tax evasion) at one point in time affects the social norm of paying taxes, i.e., the individual's beliefs about others paying taxes, $B_i(M1)$. This will affect the individual's own action assessments, $(DBO)_{ij}$, and likelihood of paying taxes. Individual action: *Ceteris paribus*, the likelihood of paying taxes is reduced (the individual 'illegally' reduces her tax liabilities, A_{i1}) Social outcome: T_1 is further increased.	(1)
$M2 \Rightarrow B_i\,(M2) \Rightarrow (DBO)_{ij} \Rightarrow A_{i2} \Rightarrow T_2$	An increase in the prevalence of T_2 (tax avoidance) at one point in time affects the social norm of paying taxes, i.e., the individual's beliefs about others legally paying all their taxes, $B_i(M2)$. This will affect the individual's own action assessments, $(DBO)_{ij}$, and likelihood of paying taxes. Individual action: *Ceteris paribus*, the likelihood of paying taxes is reduced (the individual 'legally' reduces her tax liabilities, A_{i2}) Social outcome: T_2 is further increased.	(2)

[16] To avoid any misunderstanding, it should be pointed out that the link between **A** and **T** in Table 1.2 is type specific. The prevalence of tax evasion only can change as the result of individuals' evasion decisions. Hence **A1** influences **T1** but **A2** cannot influence **T1** unless it influences **A1** (and vice versa for tax avoidance).

TYPE OF MECHANISM:	DESCRIPTION:	ID:
$M2 \Rightarrow B_i\,(M2) \Rightarrow (DBO)_{ij} \Rightarrow A_{i1} \Rightarrow T_1$	An increase in the prevalence of T_2 (tax avoidance) at one point in time affects the social norm of paying taxes, i.e. the individual's beliefs about others legally paying all their taxes, B_i(M2). This will affect the individual's own action assessments, $(DBO)_{ij}$, and likelihood of paying taxes. Individual action: *Ceteris paribus*, the likelihood of paying taxes is reduced (the individual 'illegally' reduces her tax liabilities, A_{i1}) Social outcome: T_1 is further increased.	(3)
$M1 \Rightarrow B_i\,(M1) \Rightarrow (DBO)_{ij} \Rightarrow A_{i2} \Rightarrow T_2$	An increase in the prevalence of T_1 (tax evasion) at one point in time affects the social norm of paying taxes, i.e. the individual's beliefs about others paying taxes, B_i(M1). This will affect the individual's own action assessments, $(DBO)_{ij}$, and likelihood of paying taxes. Individual action: *Ceteris paribus*, the likelihood of paying taxes is reduced (the individual 'legally' reduces her tax liabilities, A_{i2}) Social outcome: T_2 is further increased.	(4)
$M3 \Rightarrow B_i\,(M3) \Rightarrow (DBO)_{ij} \Rightarrow A_{i1} \Rightarrow T_1$	An increase in the enforcement level of tax law (penalties and audit rates, M3) affects the perceived risk of evading taxes and this affects the individual's action assessments, $(DBO)_{ij}$, and likelihood of paying taxes. Individual action: *Ceteris paribus*, the likelihood of paying taxes is increased (the individual pays her tax liabilities without evading taxes, A_{i1}) Social outcome: T_1 is decreased.	(5)
$M3 \Rightarrow B_i\,(M3) \Rightarrow (DBO)_{ij} \Rightarrow A_{i2} \Rightarrow T_2$	An increase in the enforcement level of tax law (penalties and audit rates, M3) affects the perceived risk of avoiding taxes and this affects the individual's action assessments, $(DBO)_{ij}$, and likelihood of paying taxes. Individual action: Ceteris paribus, the likelihood of paying taxes is increased (the individual pays her tax liabilities without legally avoiding taxes, A_{i2}.). Social outcome: T_2 is decreased.	(6)
$M4 \Rightarrow B_i\,(M4) \Rightarrow (DBO)_{ij} \Rightarrow A_{i1} \Rightarrow T_1$	How 'fair' individuals perceive the tax system (M4) to be at one point in time affects the social norm of paying taxes. Therefore, the higher the progressivity of the tax system, the more incentives (D_{ij}) the individual has to evade/avoid taxes. Individual action: *Ceteris paribus*, the likelihood of paying taxes is reduced (the individual 'illegally' reduces her tax liabilities, A_{i1}) Social outcome: T_1 is further decreased.	(7)
$M4 \Rightarrow B_i\,(M4) \Rightarrow (DBO)_{ij} \Rightarrow A_{i2} \Rightarrow T_2$	How 'fair' individuals perceive the tax system (M4) to be at one point in time affects the social norm of paying taxes. Therefore, the higher the progressivity of the tax system, the more	(8)

TYPE OF MECHANISM:	DESCRIPTION:	ID:
	incentives (D_{ij}) the individual has to evade/avoid taxes. Individual action: *Ceteris paribus*, the likelihood of paying taxes is reduced (the individual 'legally' reduces her tax liabilities, A_{i2}) Social outcome: T_2 is further decreased.	
$M5 \Rightarrow B_i\ (M5) \Rightarrow (DBO)_{ij} \Rightarrow A_{i1} \Rightarrow T_1$	The "transparency" of the tax code affects the individual's beliefs about the complexity (or knowledge) of the tax code, B_i (M5), and this influences the individual's evasion opportunities (O_{i1}), which in turn is likely to influence the individual's decision whether or not to evade taxes, and thereby also the prevalence of tax evasion in society at large. Individual action: *Ceteris paribus*, the likelihood of evading is increased (the individual illegally reduces her tax liabilities, A_{i1}) Social outcome: T_1 is further increased.	(9)
$M5 \Rightarrow B_i\ (M5) \Rightarrow (DBO)_{ij} \Rightarrow A_{i2} \Rightarrow T_2$	The "transparency" of the tax code affects the individual's beliefs about the complexity (or knowledge) of the tax code, B_i (M5), and this influences the individual's avoidance opportunities (O_{i2}), which in turn is likely to influence the individual's decision whether or not to avoid taxes, and thereby also the prevalence of tax avoidance in society at large. Individual action: *Ceteris paribus*, the likelihood of avoiding is increased (the individual illegally reduces her tax liabilities, A_{i1}) Social outcome: T_2 is further increased.	(10)
$M6 \Rightarrow B_i\ (M6) \Rightarrow (DBO)_{ij} \Rightarrow A_{i1} \Rightarrow T_1$	How legitimate people perceive the government to be (M6) affects the individual's beliefs about how appropriately the government make use of tax revenue B_i(M6) and their subsequent action assessments, $(DBO)_{ij}$, about paying taxes. Therefore this is likely to have an impact on the overall level of tax avoidance and evasion. Individual action: *Ceteris paribus*, the likelihood of paying taxes is reduced (the individual illegally reduces her tax liabilities, A_{i1}) Social outcome: T_1 is further increased.	(11)
$M6 \Rightarrow B_i\ (M6) \Rightarrow (DBO)_{ij} \Rightarrow A_{i2} \Rightarrow T_2$	How legitimate people perceive the government to be (M6) affects the individual's beliefs about how appropriately the government make use of tax revenue B_i(M6) and their subsequent action assessments, $(DBO)_{ij}$, about paying taxes. Therefore this is likely to have an impact on the overall level of tax avoidance and evasion. Individual action: *Ceteris paribus*, the likelihood of paying taxes is reduced (the individual legally reduces her tax liabilities, A_{i2}) Social outcome: T_2 is further increased.	(12)

Let us start with mechanisms 1 and 2. One way in which they might operate is via the cognitive or belief dimension, $\mathbf{M1} \Rightarrow \mathbf{B}_i\ \mathbf{(M1)} \Rightarrow \mathbf{B}_{ij} \Rightarrow \mathbf{A}_{i1} \Rightarrow \mathbf{T}_1$ and $\mathbf{M2} \Rightarrow \mathbf{B}_i\ \mathbf{(M2)} \Rightarrow \mathbf{B}_{ij} \Rightarrow \mathbf{A}_{i2} \Rightarrow \mathbf{T}_2$. That is to say, according to this form of endogenous feedback-mechanism, the extent of evasion among others influence individuals' beliefs in such a way that they become more likely to evade.

Numerous experimental studies have established the importance of this kind of belief-based mechanism for individuals' contributions to public goods. As already alluded to above, these experiments have shown that most people are neither egoists, as assumed in traditional economic models, nor altruists. Instead, most individuals are *conditional altruists* who behave nicely and contribute to public goods as long as they know or believe that others are doing the same (Gintis et al. 2005; see Fehr and Gintis 2007). If a conditional altruist believes that others are contributing to a pubic good (e.g., by paying the taxes they are supposed to pay), they are likely to do the same even if they would be better off economically by being free riders and evading taxes. But if a conditional altruist believes that others are not contributing to the public good, neither will he. The fact that a conditional altruist is so sensitive to the behaviour of others means that social-contagion processes are likely to be important for explaining variations in tax behaviour.

One interesting field-based test of this belief-mechanism is that of Coleman (2007). Coleman and his team sent out a letter to a random sample of approximately 20,000 taxpayers in Minnesota with the following content:

> According to a recent public opinion survey, many Minnesotans believe other people routinely cheat on their taxes. This is not true, however. Audits by the Internal Revenue Service show that people who file tax returns report correctly and pay voluntarily 93 per cent of the income taxes they owe. Most taxpayers file their returns accurately and on time. Although some taxpayers owe money because of minor errors, a small number of taxpayers who deliberately cheat owe the bulk of unpaid taxes (p. 2).

When comparing the amount of income reported and the amount of state taxes paid among those who received the letter and those who did not (a control group), the study found that the letter had a statistically significant effect on the individuals' tax behaviour. As predicted by the theories of Fehr and others, changing the beliefs about the tax compliance of others made individuals' less likely to evade (Wenzel 2005b for a similar type of field experiment with similar results conducted in Australia; see also Wenzel 2005a).

Now let us turn to mechanisms 3 and 4. They are special in the sense that they are concerned with a "causal leakage" within the cognitive domain between tax avoidance and tax evasion, i.e., mechanisms that make individuals who engage in legal tax avoidance more prone to also engage in illegal tax evasion and vice versa (for a more detailed analysis of such mechanisms, see Hedström and Ibarra 2010). Despite the legal distinction between tax evasion and tax avoidance, the two types of activities are not clearly demarcated from one another (Cowell 1990). The fact that they are closely related activities means that knowledge gained in one domain can be useful also in the other domain, and this sort of knowledge transfer is what these mechanisms are all about. For example, individuals who are engaged in tax avoidance learn a lot about the blurred line between legal and illegal tax behaviour, and this knowledge can be of direct relevance for their ability to successfully engage in tax evasion.

Mechanism 3, $\mathbf{M2} \Rightarrow \mathbf{B}_i\ \mathbf{(M2)} \Rightarrow \mathbf{(DBO)}_{ij} \Rightarrow \mathbf{A}_{i1} \Rightarrow \mathbf{T}_1$, states that if the tax avoidance of others makes an individual more likely to engage in tax avoidance (through any of the relevant mechanisms detailed in the table), this can also affect the opportunities for tax evasion in such a way that the individual becomes more likely to evade. Tax avoidance prevalence might influence tax evasion by influencing the evasion-relevant opportunities, i.e., since successful tax avoidance can generate more resources for the individual in question, those resources open up even more opportunities for tax evasion, e.g., by allowing the individual in question to hire expensive tax lawyers. Therefore, this causal leakage links the avoidance-relevant desires, beliefs, and opportunities, on the one hand, and the evasion relevant desires, beliefs, and opportunities on the other.[17]

Let us then turn to mechanisms 5 and 6. They link various aspects of the institutional and legal environment to individuals' tax behaviour. These mechanisms, $\mathbf{M3} \Rightarrow \mathbf{B}_i\ \mathbf{(M3)} \Rightarrow \mathbf{(DBO)}_{ij} \Rightarrow \mathbf{A}_{i1} \Rightarrow \mathbf{T}_1$, and $\mathbf{M3} \Rightarrow \mathbf{B}_i\ \mathbf{(M3)} \Rightarrow \mathbf{(DBO)}_{ij} \Rightarrow \mathbf{A}_{i2} \Rightarrow \mathbf{T}_2$, are also concerned with one of the traditional explanatory factors of the economic approach to taxation, the probability that a tax evader is detected. They state that the higher the detection

[17] I will not specifically discuss mechanism 4 here since it is identical to mechanism 3 in terms of its logics, except that it concerns the increasing extent of tax avoidance rather than tax evasion.

probability is, the less attractive the evasion alternative will appear, and the less likely an individual hence is to evade (see Spicer and Lundstedt 1976; Mason and Calvin 1978 for survey studies supporting these mechanisms).

The purely belief-based version of these mechanisms ($\mathbf{M3} \Rightarrow \mathbf{B}_i\ \mathbf{(M3)} \Rightarrow \mathbf{B}_{ij} \Rightarrow \mathbf{A}_{ij} \Rightarrow \mathbf{T}_j$) leads to a dramatically different prediction, however. While the economic approach suggests that increased enforcement leads to less evasion, the belief-based version of these mechanisms suggests that it leads to more evasion. The reason for expecting more enforcement resources to lead to more rather than less tax evasion is that increasing the enforcement resources may send a signal that tax evasion has become more prevalent because otherwise the government would not have allocated additional resources for this purpose. Sending out such a signal is likely to increase tax evasion because conditional altruists become more evasion prone if they are led to believe that tax evasion is becoming more widespread (see also Lederman 2003b; Kahan 2005; Frey and Torgler 2007). The joint net effect of the different mechanisms is unclear, i.e., it is unclear on theoretical grounds whether the intended deterrence effect exceeds the unintended effect that increases the evasion level.

Although much remains to be done in this area, there is considerable experimental and non-experimental evidence about the importance of the social mechanisms detailed above. When mechanisms such as those in 1-4 operate, cognitive and social dynamics different from those embodied in the traditional economic approach are essential for explaining the extent of tax evasion and tax avoidance. And when any of these mechanisms operate, social networks and social interactions are likely to be of importance, not only for explaining single individuals evasion/avoidance decisions but also for explaining the collective evasion/avoidance dynamics and the patterns of tax evasion/avoidance in different groups.[18]

In order to summarize this discussion, it can be useful to group these detailed mechanisms into classes of mechanisms that share important properties. One can classify mechanisms likes these into classes of mechanisms in at least two principally different ways: (1) mechanisms can be said to belong to the same class if they generate the same type of outcome, or (2) mechanisms can be said to belong to the same class if there is a family resemblance between them in terms of the way in which they are organized.

The first type of classification could be based on the information about effects on individual actions and social outcomes listed in Table 1.2. It would distinguish between four different classes of mechanisms based upon whether the mechanism concerns tax evasion or tax avoidance, and whether it leads to more or less tax evasion/avoidance than what otherwise would have been the case.

The second type of classification is subtler and potentially more useful. Following Elster (1989a) a mechanism can be said to provide a continuous and contiguous chain of causal or intentional links between the *explanans* and the *explanandum*. The explanandum is more or less the same in all of the mechanisms detailed above, i.e., acts of tax evasion or tax avoidance.

[18] For some interesting analyses along these lines, see Glaeser, Sacerdote, and Scheinkman (1996); Falk and Fischbacher (2002); and Fortin, Lacroix, and Villeval (2007).

The interesting and important differences between the mechanisms instead refer to the explanans, i.e., to the type of triggering events and the type of causal/intentional links between the triggering event and the explanandum.

An important distinction as far as the triggers are concerned is whether or not the trigger is exogenous to the rest of the mechanism. This distinction between endogenous and exogenous triggers is important because the macro processes they bring about are likely to unfold differently over time. The types of triggers discussed above all are macro-level phenomena, either changes in the institutional or legal environment of the individuals or changes in the typical behaviour of others. In the types of mechanisms focused upon here, the former types of triggers typically are exogenous to the rest of the mechanisms, while the latter types of triggers typically are endogenous,

As far as the causal/intentional links are concerned, it seems particularly important to distinguish between the following three types of causal/intentional links: (1) predominantly affective or desire-based; (2) predominantly cognitive or belief-based; and (3) predominantly structural or opportunity-based.

Using this two-dimensional classification based on type of trigger and type of causal/intentional link reduces the complex array of mechanisms detailed above to six main types with their corresponding names or labels (see Table 1.3). These abstract labels are used in order to underscore the abstract and general character of each type of mechanism. That is to say, these labels refer to types of mechanisms rather than concrete examples of specific mechanisms. The first letter identifies the type of causal/intentional links involved, and the two last letters identify the type of trigger.

Table 1.3. Classes of mechanisms essential for explaining tax evasion and tax avoidance in society at large

		Type of trigger:	
		Exogenous	*Endogenous*
Core type of causal/intentional link:	Belief –based	BEX - mechanisms	BEN- mechanisms
	Desire –based	DEX- mechanisms	DEN- mechanisms
	Opportunity-based	OEX- mechanisms	OEN- mechanisms

A *BEX mechanism* is characterized by a combination of an exogenous trigger and a belief-based link between explanans and explanandum. One concrete example of such a mechanism is when a government invests more resources into the enforcement of tax legislation (the exogenous trigger), and this sets in motion a belief-revision process in the relevant population that is such that it leads to more tax evasion than otherwise would have been observed. As discussed above, this outcome is likely to be observed when the trigger makes individuals believe that the extent of tax evasion is higher than what they believed before the triggering event.

A *DEX mechanism* is characterized by a combination of an exogenous trigger and a desire-based link between the explanans and the explanandum. One example of such a mechanism is similar to the BEX mechanism just discussed, but operates via a desire-based rather than a belief-based link between the explanans and the explanandum. Assume, for example, that the government makes the same investment of resources into the enforcement of tax legislation as in the previous example. This is not only likely to influence individuals' beliefs as discussed in the previous paragraph, but is also likely to affect how desirable they perceive tax evasion to be. If the investment is effective and leads to an increased detection risk, the expected value of evading taxes will fall and everything else being equal, this is likely to make individuals less likely to engage in such behaviour.

An *OEX mechanism* is characterized by a combination of an exogenous trigger and an opportunity-based link between the explanans and the explanandum. To stay close to the previous examples, assume that the government changes the legislation in such a way that previously existing loopholes are closed. This means that the opportunities for tax avoidance will be diminished, and everything else being the same, this is likely to make individuals less likely to engage in tax avoidance.

A *BEN mechanism* is characterized by a combination of a trigger that is endogenous to the mechanism and a belief-based link between the explanans and the explanandum. One example of such a mechanism is the traditional self-fulfilling process as analysed by Merton (1968b): Person X does Y, this is observed by others and even if they do not know why X did Y, to the extent that they believe that X or people like X typically have good reasons for doing what they do, this may affect their own beliefs in the value of doing Y in such a way that they also decide to do Y. If this is observed by yet others, it may set in motion an entirely endogenously driven belief-revision process with potentially far-reaching effect. In the case of taxation, X may refer to tax evaders and Y to stopping evading taxes.

A *DEN mechanism* is characterized by a combination of a trigger that is endogenous to the mechanism and a desire-based link between the explanans and the explanandum. Individuals' actions often are influenced by the local normative climate in which the individuals are embedded. If an individual is embedded in a local environment in which the normative pressure to pay one's taxes is strong, the individual is less likely to evade taxes that he would be in an environment with a lesser normative pressure. Since the normative pressure to pay one's taxes is weakened the more common it is that others evade taxes, a purely endogenous process, similar to the one analysed in Granovetter (1978) gradually can erode the normative climate and substantially increase the extent of tax evasion.

A *OEN mechanism* is characterized by a combination of a trigger that is endogenous to the mechanism and an opportunity-based link between the explanans and the explanandum. To the extent that the resources of those who enforce existing tax legislation is more or less constant over time, tax evasion of some are likely to increase the opportunities for successful tax evasion for others, and may therefore through an opportunity-based positive-feedback loop create a situation where tax crimes feed back onto it self. Assume as in the previous examples that some individuals start to evade taxes. Enforcement agencies then either have to concentrate their resources on some evaders or spread their resources more thinly over the entire field. In both scenarios this is likely to lead to lower detection risks for any randomly chosen evader and this is likely to increase the evasion levels.

With this brief summary of the preceding discussion in terms of six main classes of mechanisms, I will now turn to the link between micro and macro, and particularly focus upon how properties of the social networks in which individuals are embedded are likely to influence how aggregate patterns of tax evasion or tax avoidance develop over time.

1.4. Networks and the link between micro and macro: An agent-based model

Although tax researchers have paid attention to many key sociological mechanisms, they have largely ignored the role of networks in explaining variations in the extent of tax evasion and tax avoidance between different societies or between groups of individuals within one and the same society. The approach to tax behaviour used here embraces Granovetter's (1985) notion of embeddedness, and argues that individuals' tax behaviour are likely to be deeply influenced by the social networks within which they are embedded. When individuals are influenced by what other individuals are doing, even individuals who are similar to one another in all relevant respects may end up acting in very different ways (see e.g., Salganik, Dodds, and Watts 2006). Hence networks and social-influence processes become crucial for explaining why individuals do what they do. Similarly, when individuals influence one another, the effects of individuals' behaviour on aggregate outcomes can be highly non-linear. One and the same act may in one situation have no discernable effect at all on the aggregate dynamics, while in a slightly different situation it may set in motion an "avalanche" which dramatically alters the aggregate outcome (see Biggs 2005).

In order to better understand the relationship between micro mechanisms and macro outcomes, agent-based modelling (ABM) has emerged as an essential tool.[19] An ABM is a simulation model of the behaviour of a set of interacting agents. These agents are assumed to act accordingly to certain rules stipulated by the analyst, and the agents typically are assumed to be embedded in some sort of social network. The focus of the analysis usually centres on how changes in the behavioural rules and/or the structures of the networks influence the aggregate outcomes the agents generate.

Most of the research on tax evasion that uses agent-based models has been concerned with tax compliance behaviour. Mittone and Patelli (2000), Davis et al. (2003), and Bloomquist (2004), and Korobow (2007) pioneered this line of work. Based on models with multiple agent attributes, different audit probabilities, and calibrated with real data, these analyses suggest that social interaction effects may be of considerable importance and that critical-mass phenomenon also can occur in tax compliance outcomes (see also Balsa et al. 2006; Szabó et al. 2008, 2009, 2010; Zaklan et al. 2008a, 2008b, 2009; Antunes et al. 2006, 2007a, 2007b, 2007c). Among the most recent tax-related ABMs, the work of Llacer et al. (forthcoming) is

[19] For useful overviews of the role of agent-based modelling in sociology, see Macy and Willer (2002); Gilbert (2008); Macy and Flache (2009).

particularly interesting. They find, as Fortin et al. (2007) also did, that social influence processes lead to different outcomes under different deterrent conditions and that the behavioural rule of the neoclassical model tends to overestimate tax evasion levels.

The ambition behind the ABM to be used here is slightly different from previous tax-related ABMs. The ambition is not to capture the process influencing individuals' tax-evasion decisions in full detail; rather the ambition is to make a general theoretical point which has not been given due attention in the tax literature, i.e., that networks can play a crucial role in conditioning the link between micro-mechanisms and macro-outcomes. In order to illustrate this, I will present the results of three different simulation experiments (see Table 1.4). Each experiment focuses on 1000 agents who face a decision whether or not to evade taxes at 100 different points in time. The individuals are embedded in directed networks. They are influenced by those from whom they receive ties, and they influence those to whom they send ties. The three experiments are identical to one another in all relevant respects except that the agents are embedded in different types of networks: random networks, community networks, and preferential-attachment networks. The decision rule used by the agents (to be described below) as well as the initial conditions (including the density of the networks) are held constant in order to examine whether the type of network as such matters for the micro-to-macro link.

Table 1.4. Summary of the three ABM experiments.

EXPERIMENT	DESCRIPTION
1. Random network	• One thousand agents make 100 tax-evasion decisions each. • Their decisions are based on the logistic choice equation described in the text. • Ten per cent of the agents evade taxes at the outset of the analysis. • The agents are embedded in a random network with a density of .12 (see text for details on how the network was generated).
2. Community network	• One thousand agents make 100 tax-evasion decisions each. • Their decisions are based on the logistic choice equation described in the text. • Ten per cent of the agents evade taxes at the outset of the analysis. • The agents are embedded in a community network with a density of .12 (see text for details on how the network was generated).
3. Preferential attachment network	• One thousand agents make 100 tax-evasion decisions each. • Their decisions are based on the logistic choice equation described in the text. • Ten per cent of the agents evade taxes at the outset of the analysis. • The agents are embedded in a preferential-attachment network with a density of .12 (see text for details on how the network was generated.

In these agent-based simulations, agents are assumed to base their decisions on the same type of logistic regression models used in the empirical chapters of this thesis. Doing so brings the theoretical and empirical analyses closer to one another, and an advantage of the logistic model is that is has a clear decision-theoretic basis.

The decision theoretic basis of the logistic regression equation can be understood as follows (for further details see Aldrich and Nelson 1984). The agents are to choose between committing or not committing a tax crime, and the agents are assumed to have preference weights, *w*, for each alternative:

w_{i1} = agent i's propensity for committing a tax crime, and

w_{i2} = agent i's propensity for not committing a tax crime.

If we assume that the agent acts on the basis of these propensities, he/she will commit the tax crime if $w_{i1} > w_{i2}$ but not if $w_{i1} < w_{i2}$.

We assume that the agents are heterogeneous and that an agent's propensity depends, in part, on one or several variables (*X*) describing relevant properties of the agent and his/her environment, and, in part, on an idiosyncratic random factor (*v*):

$$w_{i1} = \sum a_{k1} X_{ik} + v_{i1}$$

$$w_{i2} = \sum a_{k2} X_{ik} + v_{i2}$$

The propensity to commit the crime will be greater than the propensity not to commit the crime if $w_{i1} - w_{i2} > 0$. We define Y_i^* to be identical to this difference:

$$Y_i^* = \sum (a_{k1} - a_{k2}) X_{ik} + (v_{1i} - v_{2i}).$$

And if we let $b_k = a_{k1} - a_{k2}$ and $u_i = v_{1i} - v_{2i}$, we have $Y_i^* = \sum b_k X_{ik} - u_i$. Agent i decides to commit the crime if $Y_i^* > 0$, i.e., if $u_i < \sum b_k X_{ik}$. In probabilistic terms this implies:

$$P(TaxCrime) = P(Y_i^* > 0) = P(u_i < \sum b_k X_{ik}),$$

and if it is reasonable to assume that the distribution of u_i follows a logistic distribution, which it usually is, the logistic regression framework can be used to model the way in which agents make their decisions.

More specifically, the agent-based models used here assume that the agents base their decisions on this logistic choice equation:

$$\ln\left(\frac{p_{it}}{1 - p_{it}}\right) = \alpha_i + \beta \sum q_{j,t-1}$$

where

p_{it} = agent *i*'s probability of committing a tax crime at time *t*,

α_i = agent *i*'s basic time-invariant propensity of committing a tax crime,

β = the change in agent *i*'s propensity of committing a tax crime resulting from agent *j* committing a tax crime, and

$q_{j,t-1}$ = 1 if agent *j* committed a tax crime at time t -1 *and* there was a direct link from agent *j* to agent *i*; otherwise $q_{j,t-1}$ = 0.

This equation implies that agent *i*'s propensity to commit a tax crime partly depends upon the agent's own properties (collected in a_i), and the value of a_i also reflect agent *i*'s beliefs about the probability of being caught and what social consequences this may have for *i*. In addition, agent *i*'s propensity to commit a tax crime partly depends upon the behaviour of other agents to whom the agent is linked, i.e., on the number of alters who committed tax crimes at *t*-1. At the outset of these simulations, agents are randomly assigned a_i-values from a normal distribution with a mean of -5 and a standard deviation of 2, and the value of the β-parameter is set to 2.2 and is the same for all agents. These specific parameter values were chosen to approximate the empirical estimates reported in Chapter 2. In each simulation there are 1000 agents in total, each of them make 100 decisions, and 10 per cent of the agents had committed a tax crime at the start of the analysis.

This decision-making model is simpler than the expected-utility model that was used above to characterize the core of the economic approach in that it does not explicitly consider how the probability of being caught influences the individuals' decisions. Also, it makes no distinction between the different types of influence that are likely to emanate from Alters who evaded taxes without being caught and from those who were caught. Technically it would not have been difficult to build a more complex simulation model that explicitly took such factors into account, but we would then loose the link to the empirical data since the data does not include any such information. The results of the agent-based simulations therefore should be seen as referring to a hypothetical world where there are no systematic differences between individuals in terms of detection risks and where the average detection risk does not change systematically during the course of the simulation. This assumption seems reasonable and further implies that the expected proportion of successful and unsuccessful offending Alters should be more or less the same for all Egos and hence should not have much impact on the results.

The model also does not explicate the detailed pathways through which the behaviour of some influences the behaviour of others. For example, it does not specify which mechanism of those detailed in Table 1.3 that is assumed to be at work (but the mechanism belongs to the EN-family since endogenous positive feedback is at its core). Similarly, the model does not seek to take into account ideas from labelling theory although some of them appear relevant in this context (see the discussion of the identity formation thesis of Becker (1963) and others and the performativity thesis of MacKenzie (2007) and others in chapters 2 and 3). As mentioned above, the aim of these agent-based analyses is not to capture or represent what goes on in individuals' minds; rather it is to make a general theoretical point which has not been given due attention in the tax literature, i.e., that networks can play a crucial role in conditioning the link between micro-mechanisms and macro-outcomes, and for this purpose an elaborate model of the actor is not needed. Here we use a model that assumes that social interactions matter for individuals' behaviour, and we investigate what happens in the aggregate when groups of agents, embedded in different types of networks, act and interact over extended periods of time.

Figure 1.7 shows what the three types of networks look like. In order to clearly visualize their distinct character, these networks are smaller than the networks used in the simulation (100 rather than 1000 agents/nodes) and the density of ties also is lower than in the networks used in the simulations (.07 rather than .12)

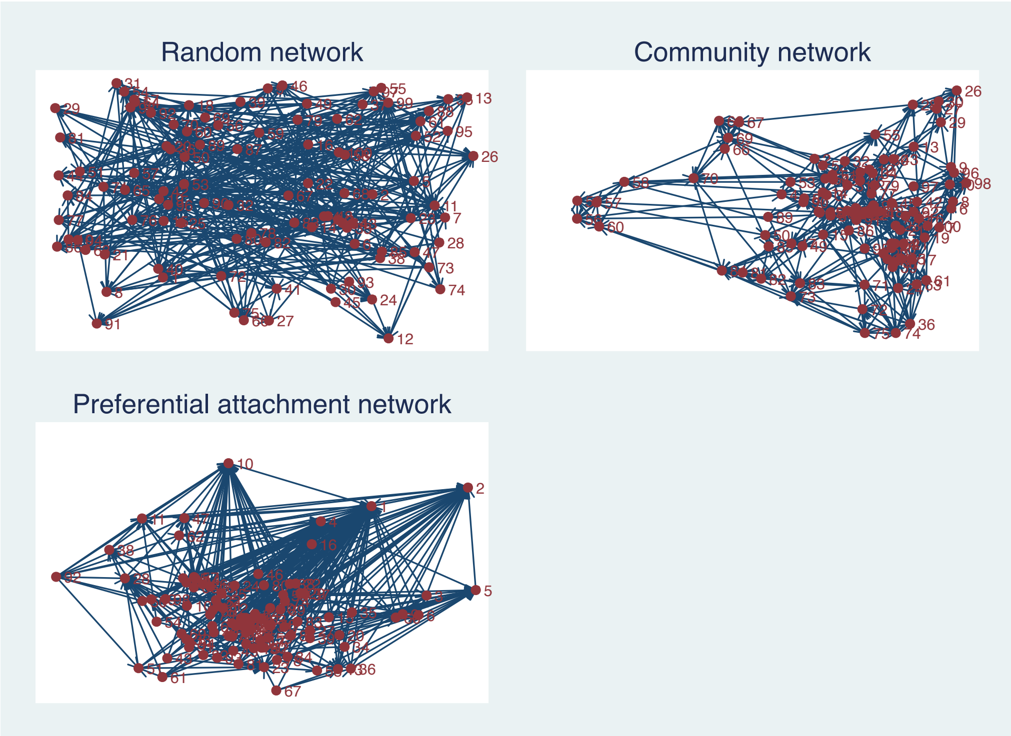

Figure 1.7. Typical random, communal, and preferential-attachment networks (100 agents/nodes and a network density of .07).

Although the networks are of the same size in terms of the number of nodes and the number of links, they differ from one another because they have been generated in different ways. One can think of the random network as having been generated by assigning links among the nodes in an entirely random fashion. For each dyad in the network we assign a directed tie with probability *p*. The random network has no social structure whatsoever and hence the northwest graph in Figure 1.7 looks like mere random clutter.

The community network is closely related to the random network but it assumes the existence of distinct social groupings within the network, and the probability of within-group links are much higher than the probability of between-group links. The group or community structure of the network is clearly visible in the northeast graph in Figure 1.7. In the simulations the 1000 agents are divided into 200 equally sized groups. The probability of a link being formed with someone from the same group is equal to .5, and the probability of a between-group link is equal to .004.

The way in which the preferential-attachment network has been generated is a bit more complex than the other two. The process is a positive feedback process through which those who are rich in terms of ties get even richer (Barabasi and Bonabeau 2003). The agents enter the system one-by-one and send links to those already in the system. The probability of an entering agent sending a link to an agent already in the system is directly proportional to the number of ties that the latter agent already has received from others. This type of process generates a highly skewed (power-law) degree distribution where a limited number of nodes/agents become highly connected network hubs. This structure is clearly visible in the southwest graph in Figure 1.7. In the simulations each agent entering the system can form between 1 and 100 links (the actual number is decided on the basis of a draw from a uniform probability distribution), and those links are directed to others based on the assignment-rule described above.[20]

[20] The simulations are done in Stata 12, in part using network-generating algorithms described in Åberg et al. (2008).

Experimental results

The experimental results reported here are results from single simulations, but these single-simulation experiments have been chosen carefully to communicate the typical result from each type of experimental setup. That is to say, the macro patterns shown here are typical of the outcomes generated by each type of experiment.

As can be seen from the simulation results presented in Figure 1.8, the social-interaction processes simulated in these experiments lead to rather sharp decreases in the prevalence of tax evasion during the first ten time periods in all three experimental conditions. At the beginning of the analysis an average of 10 per cent evaded their taxes, but this percentage had fallen to an average of approximately 1.5 per cent already after ten time periods. Once this lower level was reached, the prevalence of tax evasion remained more or less the same for the remaining 90 time periods (with the exception for some small and unsystematic random noise). Hence, these results suggest that the network structures in which the agents were embedded played no role in conditioning the relationship between micro mechanisms and macro outcomes. The macro patterns are almost identical for all three types of networks, and this suggests that the network structure was of minor importance.[21]

[21] It should be noted that these time trajectories depend upon the initial proportion evaders. That is, tipping points exist. If the initial proportion of evaders exceeds the tipping point, the proportion of evaders will increase over time. These analyses focus on the social dynamics observed in the region below the thresholds. The reason for this is that the thresholds typically are so high that they are not observed in real data. In the community network, for example, the tipping point is at approximately 19 per cent.

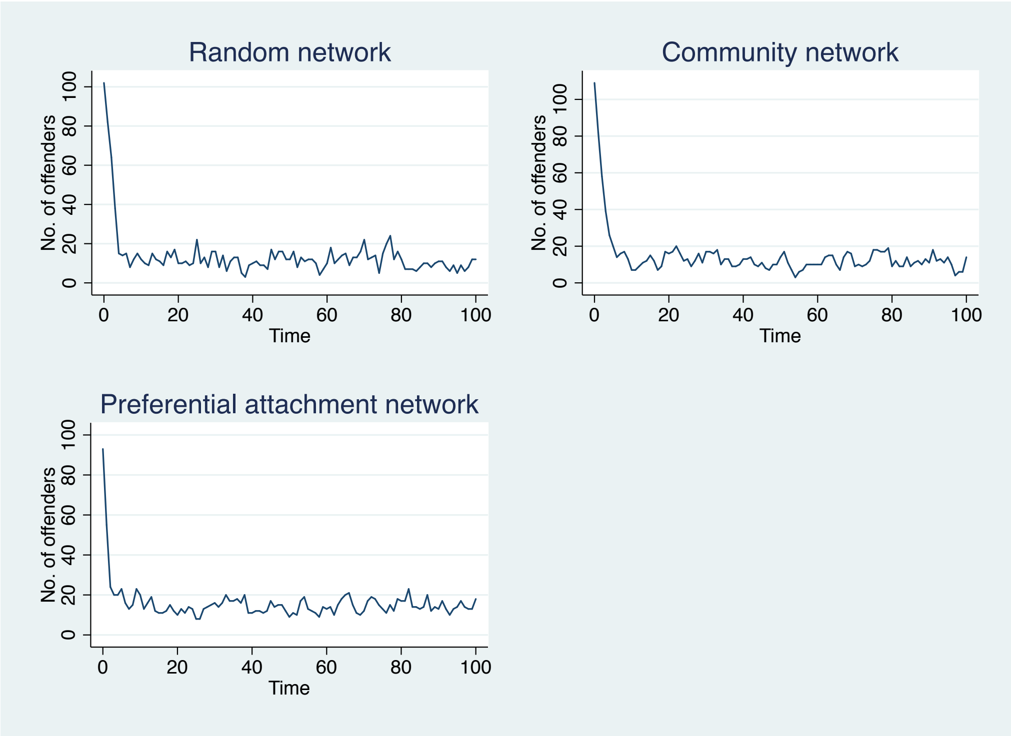

Figure 1.8. Typical time trajectories for the number of tax offenders in the agent-based simulations. The simulations assume 1000 agents who are embedded in networks with a density of .12.

The fact that the network structures had no discernable impact on the number of offenders does not mean that they lacked causal efficacy, however. The similarities between the three experimental outcomes shown in Figure 1.8 conceal an important difference between them. While the overall proportion of offenders is more or less the same irrespective of the network structure, the network structure seems to make a considerable difference for the distribution of crimes committed by the agents (see Figure 1.9).

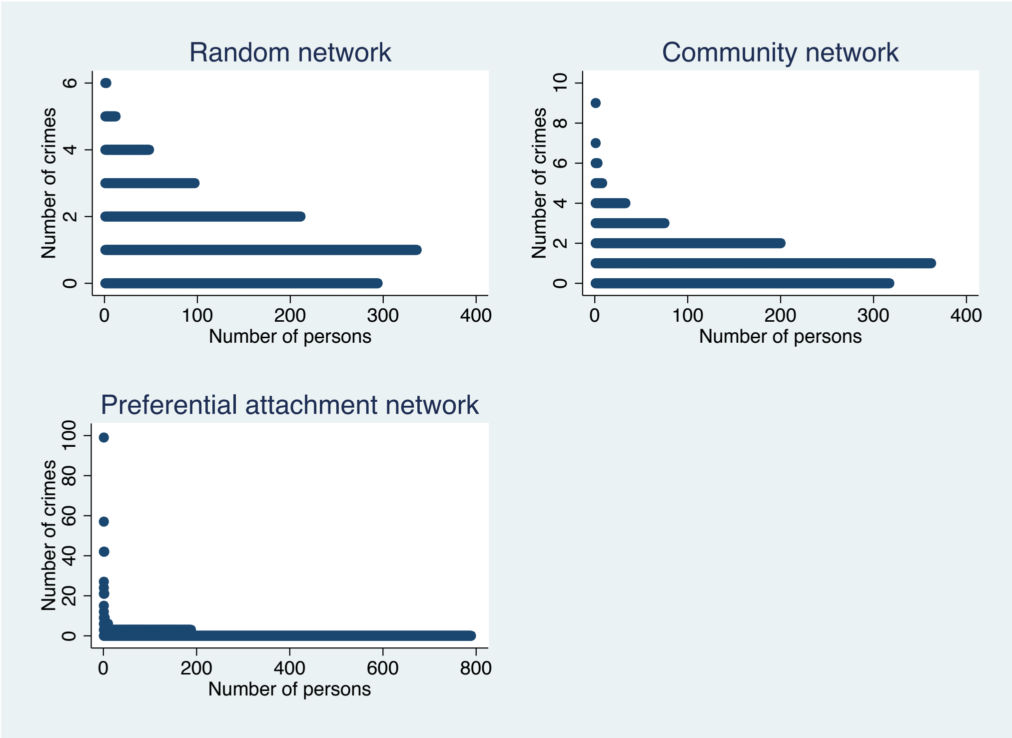

Figure 1.9. Typical distribution of repeat offenses in the agent-based simulations. The simulations assume 1000 agents who are embedded in networks with a density of .12.

When embedded in random networks, about 300 agents committed no crimes at all, 350 committed one crime, and one and the same agent committed at most six crimes. When they were embedded in the community network, the agents brought about a closely related outcome distribution. Also then, the distribution peaked at one crime, but the distribution is slightly longer-tailed than in the case of the random-network experiment.

In the preferential-attachment experiment an entirely different and empirically much more plausible distribution is generated. The distribution is highly skewed; the vast majority, about 80 per cent, commits no crimes at all, and the vast majority of those who commit crimes, commit one crime only. But there is long tail of repeat offenders, including a handful of agents who committed crimes at every second time period or more. The details of the percentages differ from simulation to simulation, but the highly skewed distributions remain the same.

In the preferential-attachment experiment, the correlation between the indegree of an agent and the total number of crimes committed over the entire period is fairly high (r = .48) which partly explains why the crime distribution has a similarly skewed shape as the degree distribution has. Agents who receive many links from others also receive many links from tax evaders, and the social influence from them makes these highly connected agents more prone to evade taxes. In the concluding chapter of this thesis I will return to these kinds of distributions, but then based upon real data. As will be seen in that chapter, the empirically observed distributions are surprisingly similar to those generated by the preferential-attachment experiment described here.

1.5. Concluding remarks.

In this chapter I have sought to provide a theoretical framework for the empirical research that is presented in later chapters. I started out with noting the curious fact that sociologists largely have ignored taxation-related issues despite the fact that taxation is of considerable social, political, and economic importance. The field instead has become dominated by economists, many of whom are working in the mainstream deterrence tradition with its strong emphasis on the explanatory importance of detection probabilities and legal penalties.

The traditional economic approach has much strength due to its rigor and precision, but its predictions have not performed particularly well. If individuals acted as suggested by this approach, tax evasion would be far more common than it actually is. This gap between actual and predicted behaviour suggests that important explanatory mechanisms have been left out of the neoclassical model.

The analytical sociological approach to tax behaviour outlined in this chapter has some similarities with the economic approach in that it emphasizes the importance of clarity and precision, and that it underscores the importance of clearly detailed micro-foundations. It differs from the economic approach, however, by considering many other mechanisms than those typically focused on by those working within the traditional economic tradition. The analytical approach is particularly concerned with social interactions and social dynamics, and is much more concerned with the empirical realism of proposed explanations than what often is the case among those working in the economic tradition.

In this chapter I specified a series of social mechanisms likely to be of importance for explaining variations in tax behaviour between different groups or societies. Most of these mechanisms are social in the sense that they refer to non-economic aspects of tax behaviour and in that they generate social behaviour in the traditional Weberian meaning of the term (Weber 1978). When these mechanisms are in operation an individual's tax behaviour is influenced by the tax behaviour of others, and the mechanisms detailed in the chapter differ from one another in terms of how this influence is transmitted. Some mechanisms operate via the structural realm, others via the cognitive realm, and yet others via the affective realm. These social mechanisms will guide the empirical analyses presented in subsequent chapters.

In the final sections of the chapter I also examined how different types of networks are likely to influence the macro-level evasion dynamics. I used an agent based simulation model that brought to the fore interesting macro-level outcomes that would have been difficult to gauge without doing these simulation analyses. The results of the simulations suggested that networks did not matter much for the prevalence of tax evasion but that they had a considerable impact on the concentration of criminal activities, including tax crimes, within certain groups of individuals. These results will serve as the backdrop for the empirical analyses in the next two chapters, one of which focuses on the effect of kinship networks on individuals' crime propensities, and one which focuses on the mechanisms that explain why individuals are more prone to commit tax crimes if they have committed such crimes in the past.

Chapter 2. Social interactions and the transmission of tax evasion and other types of economic crimes within families

2.1. Introduction

As discussed in Chapter 1, a range of mechanisms suggest that social interactions may be important for explaining why some individuals and not others commit tax evasion and other types of economic crimes. If family, friends, and/or acquaintances evade taxes or commit other types of economic crimes, this can influence an individual's beliefs, norms, and opportunities in such a way that she commits a crime she otherwise would not have committed. In this chapter, the focus is on the explanatory role of family and kinship ties because the family is an important social-interaction domain and therefore also an important test case. If social interactions are important, one should expect such effects to be clearly visible in the family domain since the family is of such importance for the way in which social life and social interactions are organized. The corollary to this is that if one does not observe such effects in the family domain, the likelihood of observing them in other domains is not very high.

As far as I am aware of, this is the first large-scale study of family and kinship influences on tax evasion and other types of economic crimes. The lack of research on this topic largely is due to the difficulty of studying rare acts like these with traditional survey data. Due to the rarity of tax evasion and other types of economic crimes, also very large surveys are unlikely to include more than a handful of respondents who have committed such crimes. In this chapter I therefore use unique large-scale population-level data to partially overcome this problem.

The importance of family influences has been examined for many other types of crime, however. David Farrington, one of the leading researchers in this area, summarized the general findings on family influence as follows: "There is no doubt that offending runs in families. Criminal parents tend to have criminal children" (Farrington, Coid, and Murray 2009: 109; see also van de Rakt 2011 for a summary of the literature on family influences). Although this chapter is motivated by the belief that this finding holds true also for tax evasion and other types of economic crimes, some caution is called for because most of the existing research on family influence has focused on violent crimes and various forms of antisocial behaviour. In their article on intergenerational transmission of antisocial behaviour, Smith and Farrington (2004) identify four classes of mechanisms relevant for explaining the observed link between parents' and children's offending: (1) similarly deprived environments; (2) biological or genetic factors; (3) similar peer and partner choices; and (4) exposure to similar parenting and socialization practices. Although one should not rule out these types of mechanisms on a priori grounds, particularly since they are known to be important for explaining other types of crimes, given past research on tax evasion and other types of economic crimes, they do not appear to be the main explanatory contenders. As discussed in Chapter 1, it seems much more likely that belief, desire, and opportunity-based mechanisms of a more contemporaneous character do most of the explanatory work.[22]

The chapter is organized as follows: First I present the core hypotheses to be tested, which concern how a focal individual's likelihood of evading taxes or committing other types of economic crimes are likely to be influenced by someone else in the family committing such crimes. Next I describe the data, the core variables, and the empirical strategy I have adopted. Thereafter I present the results from a set of event-history analyses that seek to shed light on the likely mechanisms at work. The chapter concludes with a general discussion of the implications and the limitations of the results presented here.

2.2. Mechanisms and hypotheses.

As mentioned above, because of its focus on violent crimes and antisocial behaviour, previous research on family influences to a large extent have been concerned with explanatory factors related to dysfunctional families and deprived social settings, and with biological mechanisms that pass on causally relevant personality traits from one generation to another (e.g., Frisell, Lichtenstein, and Langstrom 2011). In this chapter the main focus instead is on the criminal offender as a decision-maker whose choices

[22] Smith and Farrington's first mechanism about deprived environments of course is related to the opportunity mechanisms focused upon in this thesis. Individuals from socially deprived environments tend to have less advantageous non-criminal alternatives than those from more prosperous environments and this makes the criminal alternative more attractive in relative terms and therefore more likely to be chosen.

whether or not to evade taxes or commit other types of economic crimes are influenced by the social environment in which he/she is embedded. The approach adopted here embraces Granovetter's (1985) notion of embeddedness and argues that an individual's behaviour often is deeply influenced by those with whom the individual is linked through various network ties. That is to say, I take my point of departure in a model of the actor as a socially embedded individual whose beliefs, norms, values, and opportunities are shaped by the behaviour of those with whom the individual interacts.

As mentioned above, in this chapter the focus is on one specific macro-level cause; the prevalence of tax evasion and other types of economic crimes among family members. As discussed in Chapter 1, "macro" here refers to properties of a collectivity of actors that is not definable for any single member of the collectivity (see also Hedström 2005). Properties describing the kin group hence are macro properties according to this definition, although "meso properties" perhaps would be more in line with existing vocabulary when focusing on "small" macro entities such as family or kinship systems.

Figure 2.1 illustrates the causal pathways I believe to be particularly important for explaining tax evasion and other types of economic crimes. Moving from the right-hand to the left-hand of the figure, it draws attention to five important aspects of the causal process:

1. In order to explain the extent and dynamics of tax evasion and other types of economic crimes in society at large, it is essential to focus on individuals' decisions whether or not to commit such crimes.
2. In order to explain an individual's decision whether or not to commit a crime, one must relate the decision to the individual's desires, beliefs, and opportunities. Only individuals who have an opportunity to commit a crime and who believe that doing so will bring about a desired outcome are likely to commit a crime.
3. An individual's beliefs about the prevalence of tax evasion in the individual's relevant reference group (or any other relevant macro cause) is likely to influence the individual's decision by influencing the individual's desires (norms, tax morale, etc.), as well as the individual's consequence-related beliefs (beliefs about the likelihood of being caught, beliefs about the likely reactions of significant others if caught, etc.). These beliefs are likely to be of explanatory importance whether or not they are true, thus echoing the insights of the so-called Thomas Theorem, "If men define situations as real, they are real in their consequences" (Merton 1995: 380).
4. Although the correctness of the individual's beliefs does not matter when it comes to explaining the individual's actions, the beliefs, of course, reflect the true state of the world that they refer to, but often imperfectly so.
5. In addition to influencing individuals' beliefs, the true state of the macro environment in which the individual is embedded, also can directly influence the individual's desires, consequence-related beliefs, and opportunities. For example, the more tax-evading kin an individual has, the more likely it is that the individual will learn new

tax evasion strategies from them. This information expands the individual's opportunity set, and is likely to increase the individual's likelihood of evading taxes (see also Korobow et al 2007).

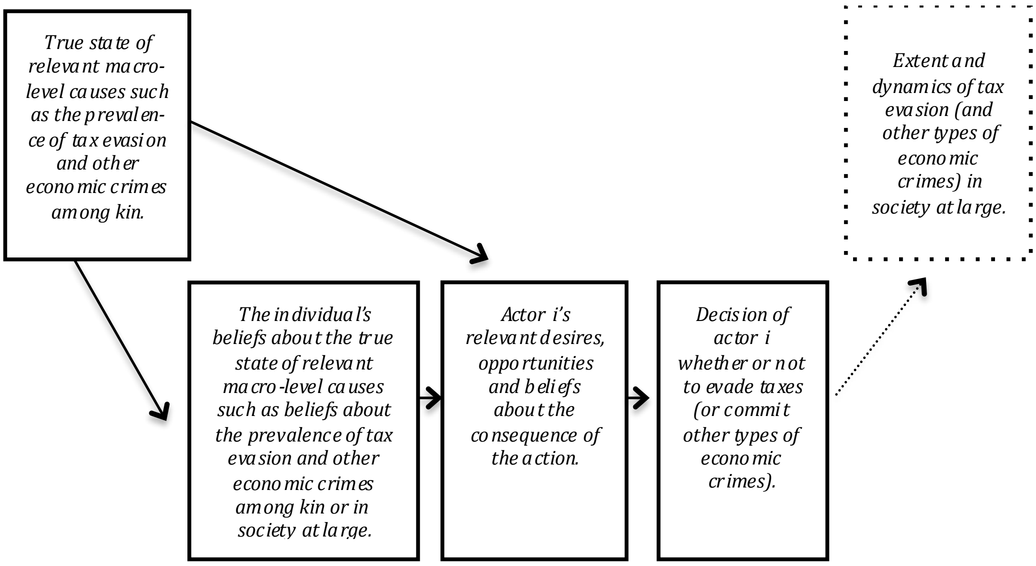

Figure 2.1. Causal pathways linking crime among kin to the focal individual's crime propensity.

As far as the third item in this list is concerned, Fehr's research has shown that close to 50 per cent of individuals are strong reciprocators (conditional altruists) who contribute to a public good (e.g., paying their taxes) if they believe that others do the same (see Fehr and Gintis 2007 for an overview). But if they do not believe that others contribute to the public good, neither will they. Because of this mechanism, the prevalence of criminal kin may affect the focal individual's crime propensity if it influences the individual's beliefs about the prevalence of tax evasion at large (see also Kahan 2005).

To decisively establish the type of mechanisms at work is a daunting task and the data requirements are enormous. Not only would we need longitudinal data on the behaviour of a large number of potential tax evaders, we would also need fine-grained data on their opportunities, attitudes, cognitions, etc., as well as behavioural data on the individuals with whom they interact. Needless to say, such data does not exist today and is not likely to exist for many years to come. Researchers in this area therefore are forced to try to solve the causal puzzle with pieces originated from rather different types of research such as statistical analyses of large-scale databases, experimental work, and ethnographic research. In this chapter, because of my interest in large-scale social processes, I use quantitative data and focus on the general behavioural aspects of family influence. Although of crucial importance for understanding the detailed mechanisms at work, I leave the fine-grained research on the formation of individuals' action-relevant opportunities and mental states to those working in more micro-oriented traditions.

My analyses focus on the behavioural aspects of the model depicted in Figure 2.1, i.e., on whether crime among kin influences a focal individual's crime propensity (once we have controlled for likely confounders). Information on the intervening factors mentioned in Figure 2.1 is not available in the data and hence cannot be part of the statistical analysis, but they will be referred to when interpreting the observed associations.

The empirical analyses seek to test three general hypotheses. The first core hypothesis to be tested is whether there indeed is a relationship between the crimes of kin and the crime propensity of the focal individual:

H1: Crime among kin influences the focal individual's propensity to evade taxes and/or commit other types of economic crimes.

This hypothesis intentionally avoids any reference to the directionality of the relationship because different sub-mechanisms are likely to bring about different reactions in different individuals. For this reason I specify the following two, seemingly contradictory sub-hypotheses:

H1.1: Crime among kin increases the focal individual's propensity to evade taxes and/or to commit other types of economic crimes.

H1.2: Crime among kin decreases the focal individual's propensity to evade taxes and/or to commit other types of economic crimes.

These two hypotheses are not contradictory, however, because they are likely to hold true under different sets of circumstances. I expect **H1.1** to hold true:

1. if crimes of other family members make crime into a cognitively more salient alternative for the focal individual (e.g., Wikström et al 2012);
2. if individuals learn how to commit criminal acts from their criminal kin (as implied by Akers' 1973 differential association/social-learning theory);
3. if having criminal kin lowers the expected social costs of being apprehended (as suggested by Latane's 1981 social-impact theory for example as well as by Paternoster et al's 2012 experimental results); and

4. if individual's beliefs about the proportion of criminal offenders in the population at large are disproportionally influenced by the proportion of criminal offenders among kin (as suggested by Tversky and Kahneman's 1973 availability heuristic).[23]

And **H1.2** is expected to hold true:

1. if the focal individual's beliefs about the probability of being detected is disproportionally influenced by the proportion of detected criminal offenders among kin (as implied by the availability heuristic); and
2. if general deterrence works. i.e., if observing how police investigations, social stigmatization processes, and legal penalties affect the lives of criminal kin make the focal individual less likely to commit an economic crime.

The direction of the combined effect of **H1.1** and **H1.2** is unknown, however, and is likely to vary between different individuals. With the type of large-scale behavioural data used here it is impossible to identify the specific conditions under which **H1.1** and **H1.2** dominate. However, as suggested by Sherif (1936) and others, individuals tend to be more influenced by others in situations characterized by a great deal of uncertainty. For that reason, it seems likely that **H1.2** will be less likely to hold true among individuals who already have a criminal record of their own. Such individuals have their own first-hand information about the probabilities of being detected and about the social and economic consequences of being caught, and one would therefore expect their beliefs about such matters to

[23] In addition to these cognitive mechanisms, various biological mechanisms also can produce these sorts of patterns. See Rowe (2002) for a detailed discussion.

be less influenced by the experiences of kin. Translated into an empirically testable hypothesis, this means that we should expect to observe a negative statistical interaction effect between the focal individual's past crime record and the prevalence of criminal offenders among kin:

> **H2**: Crime among kin will have less impact on the focal individual's propensity to evade taxes or commit other types of economic crimes if the individual has a crime record of his/her own.

The third hypothesis to be tested concerns the relative importance of the cognitive and evaluative dimensions when it comes to explaining these types of crime. Although the dataset does not include any information on individual's beliefs and values, it nevertheless can be used to shed some light on the issue. If **H1.1** is supported by the data, there can be at least two different reasons for why we observe a positive relationship between the crime of kin and the crime propensity of the individual. On the one hand, it could reflect a change in the normative environment in which individuals are embedded, i.e., if there are criminal offenders among kin, the less law-abiding normative pressure the focal individual in question will be exposed to, and this may increase the individual's crime propensity. On the other hand, it could reflect the operation of cognitive mechanisms, e.g., that the individual in question learns the tricks-of-the-trade from kin, and this may increase the individual's crime propensity. If the cognitive mechanism is dominant, one would expect the kin influence to be highly crime specific because most of the skills needed for tax evasion only can be gained from kin who themselves have engaged in tax evasion. But if it rather were the normative mechanism that were at work, one would expect a much more generalized influence because changes in the normative environment can result from any kind of crime committed by a kin. For example, if a kin commits a robbery or a violent crime, this is not likely to have any effect on tax evasion via the cognitive dimension, but it may change the focal individual's normative environment in such a way that it increases his/her probability of evading taxes. Thus, I seek to test the following hypothesis, which I expect to hold true if the cognitive mechanism dominates:

> **H3**: The probability of the focal individual committing a crime of type X is more influenced by kin committing crime of type X than their committing any other type of crime.

H1, **H2**, and **H3** are the core hypotheses that will guide the event-history analyses. In addition, several other hypotheses guide the inclusion of control variables, but these hypotheses will be introduced when the statistical model is presented in the next section.

2.3. Data and empirical research strategy

2.3.1. The Stockholm Database

Statistics Sweden (SCB) assembled the Stockholm database by merging a large number of administrative and demographic registers. This is possible since all residents in Sweden have a personal ID number that is used by all government authorities, local and central, when they store information about the individuals they are in contact with. Merging data from different registers hence is straightforward. Since Sweden has a large welfare state in which residents often come into contact with different government authorities, the database also contains information from numerous different spheres of individuals' lives. The quality of the data is high and missing data is largely absent.[24]

The main part of the data comes from a database called LISA (see SCB 2009 for a description of this database). We have complemented the LISA database with information from various other registers.[25] Given the focus of this study, the most important addition is that we have gained access to the crime records of all adult individuals in Stockholm County (more on that below).

The dataset that the analyses reported below are based upon, include all persons, 16 years or older, who resided in Stockholm County during at least one of the years 1990 to 2003. All in all, 1,967,993 unique persons and 23,029,738 unique person-year observations fulfil these criteria and are included in the dataset.

We received the crime data from BRÅ, the Swedish Crime Prevention Council, which is the government authority responsible for producing official crime statistics. The data refers to crimes for which an individual is "skäligen misstänkt", i.e., reasonably suspected, after the police, the

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[24] The missing data that exist refers to information that has not been registered by the authority in question for some individuals. When data is missing the reason typically is that the data refers to events or something that was acquired outside of Sweden. Educational levels for some immigrants are missing for that reason, for example.

[25] "We" here refers to a project housed at the Department of Sociology at Stockholm University under the direction of Peter Hedström and Ryszard Szulkin.

prosecutor, and/or the customs authority finished their investigations. “Skäligen misstänkt” is an established legal term in Sweden and implies that there is strong factual evidence suggesting that an individual has committed the crime in question. The gravity of the suspicion is demonstrated by the fact that being “skäligen misstänkt” for a crime is sufficient ground for incarcerating the person for up to 14 days. Most criminologists in Sweden consider this to be the crime variable of choice because it is perceived to better reflect the actual criminal behaviour of individuals than variables based on court decisions, for example.

The crime data includes a detailed four-digit code that makes it possible to identify rather precisely what kind of crime an individual has committed (see BRÅ 2010). All in all, there are 371 unique crime codes in the data set.

Before proceeding to the empirical analyses it is worth emphasizing that the true number of crimes and criminal offenders undoubtedly is higher than what is reported here. Many crimes are not reported to the authorities and for many crimes no one is ever apprehended or suspected. Although the crime levels reported here hence are conservative, there is no reason to think that the associations between different variables reported here are biased by this, and it is these relationships that is my main interest.

The focus of this chapter is on tax evasion, but in the empirical analyses I also analyse “bookkeeping crimes” and “other types of economic crimes”. “Other economic crimes” consist of other types of economic crimes than tax evasion and bookkeeping crimes, i.e., embezzlement, counterfeiting, extortion, and crimes against creditors. The reason for including bookkeeping crimes in the analyses is that many bookkeeping crimes are motivated by a desire to evade taxes, and hence bookkeeping crimes in many instances is a form of tax evasion. I include analyses of "other economic crimes" in order to examine whether the results concerning tax evasion and bookkeeping crimes are generalizable to a wider class of economically motivated white-collar crimes.

The kin variable is of crucial importance for these analyses. In this database one can identify the full range of kinship relations. To simply the analysis I group kin relations into four categories. One category is the spouse of the focal individual. Another category consists of the children and grandchildren of the focal individual. The remaining two categories are proximity-based, and I refer to them as "close" and "distant" kin. A person is considered to be close kin if he/she is the parent, grandparent, or sibling of the focal individual, and aunts, parents in law, and brothers and sisters in law are considered distant kin.

Since the dataset only includes individuals who resided in Stockholm County at least once during the years 1990 to 2003, I only will be able to examine kin or family influences originating from those who resided in Stockholm County during at least one of those years. The data allows us to identify parents and grandparents, however, even if they never resided in Stockholm County. There is no other information about these non-Stockholm based parents and grandparents other than the kinship information, so they will not themselves be included in any of the analyses reported below, but they are crucial for identifying siblings, uncles, aunts, and other relatives who resided in Stockholm County.

2.3.2. The Model

I use discrete-time event-history models (see Allison 1982) to test the hypotheses. A discrete-time event-history model is a regular binary logistic regression model but it is estimated with data which first have been arranged in such a way that each individual contributes as many observations as the number of years he/she has been at risk of experiencing the event in question, i.e., evading taxes, bookkeeping crimes, or other types of economic crimes.

Once the data has been rearranged in this fashion, the parameters of a logistic regression model like this will be estimated:

$$\ln\left(\frac{p_{it}}{1-p_{it}}\right) = a + \sum b_k \times K_{it-1} + \sum b_x \times X_{it-1}$$

where p_{it} equals the hazard or the probability that individual i will evade taxes or commit other types of economic crimes in year t given that he/she was at risk of committing such a crime at that point in time.[26] K_{it-t} is the relevant exposure variables indicating whether the individual's kin had committed those crimes up until year t-1. X_{it-1} is a set of control variables, and a, b_k, and b_x are parameters to be estimated.

The exposure variables simply indicate whether or not at least one person of a specific kin type had committed a specific type of crime during the period from the beginning of the observation window in 1990 until year t-1. Using

[26] I only focus on the first crime of these three types of economic crimes committed by an individual. Hence, once an individual has committed the kind of crime the analysis focuses upon, he/she is removed from the risk set.

alternative exposure variables obviously would change some of the details of the results reported below, but preliminary analyses not reported here suggest that the main conclusions are robust in relation to the details in which exposure is measured.

The control variables included in these event-history models and their hypothesized effects are described in Table 2.1. In addition, a set of yearly dummy variables is included as covariates in order to control for possible period effects due to omitted variables. The “logit” command in Stata 12 has been used for estimating the parameters of the model.

Table 2.1. Description of control variables and their hypothesized effects.

CONTROL VARIABLE:	DESCRIPTION:	HYPOTHESIZED PARTIAL EFFECT:
Gender	A dummy variable distinguishing between women (=1) and men (=0).	Negative since men generally are more likely to engage in crime than women are.
Age	Four dummy variables distinguishing between the following age groups: 18-25, 26-35, 36-65, and 65+. Age is measured at the end of each calendar year.	No specific hypothesis except that the 65+ category is expected to be less prone to engage in criminal activities than the other age groups.
Single	A dummy variable distinguishing between single (=1) and married/ cohabiting with children (=0) at the end of each calendar year.	Positive since single individuals generally are more likely to engage in criminal activities than married people are.
Education	Three dummy variables based on the individual's highest level of education in a given year distinguishing between low education (less than high school), mid-level education (completed high school), and high education (at least some university education).	Negative since highly educated persons tend to be less likely to engage in criminal activities than the less educated are.
Foreign background	A dummy variable that identifies individuals with "foreign background". An individual is considered to have a "foreign background" if both of his/her parents were born outside of Sweden.	Positive since previous research shows on considerable overrepresentation of individuals with foreign background in many criminal activities.
Income	Natural logarithm of the total amount of employment and business income earned by the individual during the year in question.	Negative since previous research shows that the rich tend to be less engaged in tax evasion than the poorer are (see text for more detailed discussion).
Self employed	A dummy variable that identifies persons who had at least some income from own business during the year in question.	Positive since the self-employed have greater opportunities to withhold income from taxation than the employed have.

2.4. Results

Table 2.2a shows the parameter estimates of the event-history models and Table 2.2b the odds ratios. Let us first focus on models 1, 3, and 5 since they are the ones testing hypothesis **H1** and its sub-hypotheses **H1.1** and **H1.2**. The dependent variables are the hazards that the focal individual will evade taxes (model 1), commit a bookkeeping crime (model 3), or commit any other type of economic crime (model 5) at time *t*, given that the individual in question had not committed such a crime by *t*-1. Variables 1-10 are the control variables described in Table 2.1, and all time-varying variables are lagged one year and hence refer to time *t*-1. Variables 11-14 are the exposure variables and they indicate whether any distant kin, close kin, spouse, child or grandchild had committed these sorts of crimes by *t-1*.

As expected, the parameter estimates suggest that men are more likely to commit these types of crimes than women are. Furthermore, individuals in working age (26 to 65) are more likely to commit these kinds of crimes than those in the 18-25 age group (the excluded reference category), and those in the 65+ age group. Since having some sort of employment or self-employment is a prerequisite for being able to commit some of these types of crimes, it is not surprising that those in working age are more likely to commit these kinds of crimes. The results also show that singles are more prone to commit these crimes, that the less education an individual has, the more likely it is that he/she will commit one of these crimes, and that individuals with a foreign background are more prone to commit these types of crimes.

Table 2.2a. Event-history models of tax evasion, bookkeeping crimes, and other economic crimes. Logistic regression coefficients (and Z-values within parentheses).

	TAX EVASION		BOOKKEEPING CRIME		OTHER ECONOMIC CRIME	
	(1)	(2)	(3)	(4)	(5)	(6)
1. Gender	-1.999 (-39.09)	-1776 (-34.20)	-1.971 (-40.11)	-1.619 (-32.24)	-1.016 (-65.24)	-0.747 (-45.54)
2. Age 26-35	1.704 (19.64)	1.517 (17.76)	1.757 (21.61)	1.453 (18.20)	.498 (24.50)	.375 (18.79)
3. Age 36-65	1.795 (22.10)	1.704 (21.14)	1.691 (22.37)	1.517 (20.28)	.052 (2.89)	.020 (1.08)
4. Age 65+	-.533 (0.15)	-.338 (-2.18)	-.779 (-5.41)	-.537 (-3.69)	-2.972 (-37.50)	-2.738 (-34.91)
5. Single	.166 (4.84)	-.026 (-0.75)	.394 (11.68)	.115 (3.27)	.651 (45.97)	.450 (30.79)
6. Mid-education	-.073 (-1.82)	-.050 (-1.26)	-.109 (-2.87)	-.078 (-2.07)	-.306 (-19.37)	-.292 (-18.67)
7. High education	-.435 (-9.09)	-.300 (-6.24)	-.737 (-14.64)	-.537 (-10.59)	-1.02 (-43.21)	-.867 (-36.68)
8. Foreign	.224 (5.56)	.066 (1.62)	.245 (6.39)	.028 (0.71)	.543 (34.63)	.394 (24.59)
9. Income	-.101 (-17.05)	-.071 (-11.90)	-.176 (-34.35)	-.139 (-26.82)	-.162 (-72.57)	-.141 (-63.06)
10. Self employed	1.434 (33.67)	1.321 (30.97)	1.628 (38.22)	1.454 (33.88)	.794 (29.66)	.743 (27.57)
11. Exposed to crime from distant kin	.583 (1.01)	.638 (0.88)	-.260 (-.036)	-12.30 (-39.42)	.928 (10.09)	.830 (6.59)
12. Exposed to crime from close kin	2.000 (6.57)	1.810 (3.94)	1.809 (7.30)	2.013 (5.65)	1.318 (21.33)	1.125 (11.95)
13. Exposed to crime from spouse	3.190 (6.96)	3.689 (7.26)	3.994 (14.06)	3.900 (10.71)	2.117 (17.59)	2.150 (14.98)
14. Exposed to crime from child/grandchild	2.192 (4.86)	1.685 (2.36)	1.135 (2.25)	.392 (.39)	.630 (5.18)	.634 (4.06)
15. Criminal record		1.438 (35.75)		1.545 (42.14)		1.645 (91.76)
16. Interaction between 11 & 15		-.463 (-0.38)		12.367 (15.54)		-.147 (-0.80)
17. Interaction between 12 & 15		-.150 (-0.25)		-.844 (-1.71)		-.194 (-1.56)
18. Interaction between 13 & 15		-2.373 (-2.09)		-.537 (-.93)		-.750 (-2.89)
19. Interaction between 14 & 15		.884 (0.96)		.915 (.79)		-.294 (-1.19)
20. Constant	-7.017 (-63.90)	-7.200 (-61.31)	-6.097 (-61.74)	-6.394 (-60.07)	-5.621 (-139.5)	-5.858 (-132.1)
Log-likelihood	-32254	-31408	-31809	-30477	-146470	-139683
Pseudo R2	.078	.093	.130	.159	.088	.112

Note: N = 15,659,529; z-values are found within parentheses; annual dummies are included as control variables; and the robust Huber-White sandwich estimator (see White 1994) has been used for estimating individually clustered standard errors.

Table 2.2b. Event-history models of tax evasion, bookkeeping crimes, and other economic crimes. Odds ratios (and Z-values within parentheses).

	TAX EVASION		**BOOKKEEPING CRIME**		**OTHER ECONOMIC CRIME**	
	(1)	(2)	(3)	(4)	(5)	(6)
1. Gender	.135 (-39.09)	.169 (-34.20)	.139 (-40.11)	.198 (-32.24)	.362 (-65.24)	.474 (-45.54)
2. Age 26-35	5.496 (19.64)	4.559 (17.76)	5.795 (21.61)	4.276 (18.20)	1.645 (24.50)	1.455 (18.79)
3. Age 36-65	6.020 (22.10)	5.496 (21.14)	5.425 (22.37)	4.559 (20.28)	1.053 (2.89)	1.020 (1.08)
4. Age 65+	.587 (0.15)	.713 (-2.18)	.459 (-5.41)	.584 (-3.69)	.051 (-37.50)	.065 (-34.91)
5. Single	1.181 (4.84)	.974 (-0.75)	1.483 (11.68)	1.122 (3.27)	1.917 (45.97)	1.568 (30.79)
6. Mid-education	.930 (-1.82)	.951 (-1.26)	.897 (-2.87)	.925 (-2.07)	.736 (-19.37)	.747 (-18.67)
7. High education	.647 (-9.09)	.741 (-6.24)	.479 (-14.64)	.584 (-10.59)	.361 (-43.21)	.420 (-36.68)
8. Foreign	1.251 (5.56)	1.068 (1.62)	1.278 (6.39)	1.028 (0.71)	1.721 (34.63)	1.483 (24.59)
9. Income	.904 (-17.05)	.931 (-11.90)	.839 (-34.35)	.870 (-26.82)	.850 (-72.57)	.868 (-63.06)
10. Self employed	4.195 (33.67)	3.747 (30.97)	5.094 (38.22)	4.280 (33.88)	2.212 (29.66)	2.102 (27.57)
11. Exposed to crime from distant kin	1.791 (1.01)	1.893 (0.88)	.771 (-.036)	.000 (-39.42)	2.529 (10.09)	2.293 (6.59)
12. Exposed to crime from close kin	7.389 (6.57)	6.100 (3.94)	6.104 (7.30)	7.486 (5.65)	3.736 (21.33)	3.080 (11.95)
13. Exposed to crime from spouse	24.288 (6.96)	40.005 (7.26)	54.272 (14.06)	49.402 (10.71)	8.306 (17.59)	8.585 (14.98)
14. Exposed to crime from child/grandchild	8.953 (4.86)	5.392 (2.36)	3.111 (2.25)	1.480 (.39)	1.878 (5.18)	.634 (4.06)
15. Criminal record		4.212 (35.75)		4.688 (42.14)		5.181 (91.76)
16. Interaction between 11 & 15		.629 (-0.38)		234919 (15.54)		.863 (-0.80)
17. Interaction between 12 & 15		.861 (-0.25)		.430 (-1.71)		.824 (-1.56)
18. Interaction between 13 & 15		.093 (-2.09)		.584 (-.93)		.472 (-2.89)
19. Interaction between 14 & 15		2.421 (0.96)		2.497 (.79)		.745 (-1.19)
Log-likelihood	-32254	-31408	-31809	-30477	-146470	-139683
Pseudo R2	.078	.093	.130	.159	.088	.112

Note: N = 15,659,529; *z*-values are found within parentheses; annual dummies are included as control variables; and the robust Huber-White sandwich estimator (see White 1994) has been used for estimating individually clustered standard errors.

On purely theoretical grounds it is not obvious that the income effect should be negative since progressive taxation gives more incentives for high-earners to withhold income from taxation. This negative income effect is in line with previous research, however, and suggests that the probability to engage in tax evasion declines with increasing incomes. On the basis of these data it is not possible to identify why we observe this negative relationship, but as often noted in the literature, the rich tend to have more opportunities to engage in legal tax avoidance and this may reduce their need or inclination to engage in illegal tax evasion (c.f., Wheatcroft 1955). Their higher incomes offer them opportunities to hire tax expertise that the less well-to-do are unable to do (see also McBarnet and C. 1991; and McBarnet 2003).[27]

The self-employment variable behaves as expected, however. It is positive and highly significant, reflecting the fact that the self-employed have many more opportunities to commit tax evasion and other types of economic crimes than the employed have, and many kinds of fraud and bookkeeping crimes that only the self-employed can commit. In addition, the result may of course reflect a selection process in which individuals with low tax morale start firms in order to evade taxes.

The exposure variables (variables number 11-14) test hypotheses **H1.1** and **H1.2**. As discussed above, there are varied sets of reasons to expect that criminal activities among kin influence a focal individual's crime propensity, but it is unclear what the net result of these various influences are likely to

[27] In addition there are some reasons of a more technical nature to expect a negative income effect. Since the income variable used here is the income reported by an individual's employer to the taxation authorities (or the income reported by the individual himself if he is self-employed), many of the tax evaders may be partly outside of the regular economy and may in part support themselves by committing various kinds of economic crimes which, if successful generate incomes that are not reported to the taxation authorities. Furthermore, it seems likely that individuals, who evaded taxes in year *t*, also may have engaged in (successful) tax evasion in year *t*-1. Their low incomes in *t*-1 then could be an indicator of criminal activities during year *t*-1 and this could explain the negative partial effect of income.

be. These empirical results strongly suggest that hypothesis **H1.1** has more support in the data than hypothesis **H1.2**. With the exception of tax evasion and bookkeeping crimes among distant kin which do not seem to have any significant effect on the focal individual's risk of committing such crimes, all the other exposure effects are significant and suggest that even when controlling for all the other variables in the model, an individual's propensity to commit one of these crimes increases if a kin has committed the same type of crime in the past. The fact that the exposure effects are positive and that individuals seem to be more influenced by close than by distant kin are in line with what one would expect if social interactions and social influence were the source for the statistical association.

The reason for including models 2, 4, and 6 in Tables 2.2a and 2.2b was to test hypothesis **H2** that stated that crime among kin would have less impact on the focal individual's crime propensity if he/she had a crime record of his/her own. In order to test this hypothesis, a dummy variable was included indicating whether or not the focal individual appeared in the criminal records during the observation window from 1990 until year *t*-1.[28] In addition, interactions between this dummy variable and each of the four exposure variables were included.

The results show that individuals who have committed other types of crimes in the past are more likely to evade taxes, commit bookkeeping crimes, and commit other types of economic crimes even when controlling for all the other covariates. Although nine out of the twelve interaction effects have the

[28] Since the event-history setup means that only individuals who have not committed the type of crime being analysed prior to *t* are included in the analysis, this dummy variable identifies individuals who had committed other types of crimes by *t*-1 than the crime analysed in the model.

expected negative signs, the analyses do not allow us to draw any firm conclusions about the statistical interaction effects. As often is the case with the modelling of statistical interaction effects, multicollinearity problems are likely to arise, and that seems to have happened here. Particularly in Model 4, the standard errors are high and the parameter estimates highly unstable with respect to small changes in model specifications. The conclusion therefore is that the data does not allow for a decisive test of **H2**.[29]

The third and final hypothesis to be tested, **H3**, sheds some light on the relative importance of cognitive and normative mechanisms. As discussed above, if the main mechanism at work were of a cognitive kind, one would expect that individuals' crime propensities mostly would be influenced by kin who have committed the same kind of crime as the focal individual is considering to commit, while if the main mechanism rather were related to normative pressure, individuals' crime propensities also would be influenced by kin who committed entirely different types of crimes. This hypothesis is tested in Table 2.3 which reports the results of three event-history analyses which are identical to model 1, 3, and 5 in Tables 2.2a and 2.2b, with the exception that each of them contains additional exposure variables indicating whether kin had committed *any* type of crime prior to *t*. In addition, based on the results reported in Tables 2.2a and 2.2b, these models also include a variable indicating whether or not the focal person had a criminal record of his/her own prior to *t*.

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[29] I also estimated separate models for those with and without a criminal record of their own, but also these models appeared unstable, in part because of the small sample size in the former category.

Table 2.3. Event-history models of tax evasion, tax crimes, and economic crimes, with additional covariates for testing hypothesis **H3**. Logistic regression coefficients (and Z-values within parentheses).

	TAX EVASION	BOOKKEEPING CRIME	OTHER ECONOMIC CRIMES
1. Gender	-1.783 (-34.54)	-1.628 (-32.62)	-.763 (-46.52)
2. Age 26-35	1.519 (17.77)	1.455 (18.27)	.377 (18.83)
3. Age 36-65	1.720 (21.27)	1.535 (20.44)	.039 (2.12)
4. Age 65+	-.307 (-1.98)	-.506 (-3.48)	-2.749 (-34.46)
5. Single	-.200 (-0.56)	.123 (3.49)	.457 (31.04)
6. Mid-education	-.041 (-1.02)	-.066 (-1.76)	-.279 (-17.76)
7. High education	-.284 (-5.87)	-.517 (-10.16)	-.842 (-35.53)
8. Foreign	.060 (1.47)	.021 (0.53)	.379 (23.52)
9. Income	-.070 (-11.64)	-.138 (-26.51)	-.140 (-62.25)
10. Self employed	1.320 (30.97)	1.454 (33.89)	.741 (27.51)
11. Criminal record	1.406 (34.50)	1.519 (41.00)	1.586 (88.10)
12. Exposed to crime from distant kin	.301 (1.27)	-.766 (-1.05)	.409 (4.01)
13. Exposed to crime from close kin	1.361 (4.34)	1.197 (4.65)	.540 (8.02)
14. Exposed to crime from spouse	1.938 (3.96)	3.082 (9.45)	.994 (7.26)
15. Exposed to crime from child/grandchild	2.068 (4.52)	.908 (1.81)	.303 (2.36)
16. Exposed to any crime from distant kin	.143 (1.27)	.263 (2.67)	.301 (6.52)
17. Exposed to any crime from close kin	.377 (4.62)	.299 (4.06)	.508 (17.28)
18. Exposed to any crime from spouse	.377 (4.43)	.581 (3.80)	.883 (14.04)
19. Exposed to any crime from child/grandchild	.079 (0.82)	.110 (1.30)	.216 (4.85)
20. Constant	-7.236 (-61.52)	-6.432 (-60.29)	-5.897 (-132.51)
Log-likelihood	-31392	-30461	-139437
Pseudo R2	.094	.159	.113
Note: N = 15,659,529; z-values are found within parentheses; annual dummies are included as control variables; and the robust Huber-White sandwich estimator (see White 1994) has been used for estimating individually clustered standard errors.			

All the exposure variables have the expected positive signs, which suggests that there is some support for both the cognitive and the normative mechanism. The logit specifications of the models make it hard to compare the different effects with one another, however, and hence make it difficult to examine the strength of the support for the cognitive and the normative mechanisms. This also is true for odds ratios (see Mood 2010). For this reason, I used Stata's margins command to calculate the average marginal effect (AME) of each variable. Intuitively, the AME for one of these variables, e.g., exposure from distant kin, is computed as follows:

1. We start with the first case, and we treat that person as though he/she were exposed to tax evasion from distant kin, regardless of whether that was the case or not. We leave all other independent variables at their true values and we compute the predicted probability that this person would evade taxes.
2. Next we do the same but this time we treat the person as though he/she had not been exposed to tax evasion from distant kin, regardless of whether that was the case or not.
3. The difference in the two probabilities computed in (1) and (2) is equal to the marginal effect for that case.
4. Thereafter we repeat this process for every case in the sample, and we calculate the average of all the marginal effects. This gives the AME for the variable measuring evasion-exposure from distant kin.

The three columns of Table 2.4 contain the AMEs for tax evasion, bookkeeping crimes, and other types of economic crimes.

Table 2.4. Average marginal effects of exposure variables on tax evasion, bookkeeping crimes, and other types of economic crimes.

	TAX EVASION	BOOKKEEPING CRIME	OTHER ECONOMIC CRIMES
1. Exposed to crime in question from distant kin	.000085	-.000135*	.000676
2. Exposed to any crime from distant kin	.000037	.000075	.000475
3. Exposed to crime in question from close kin	.000695	.000578	.000953
4. Exposed to any crime from close kin	.000109	.000087	.000859
5. Exposed to crime in question from spouse	.001420	.004978	.002258
6. Exposed to any crime from spouse	.000242	.000197	.001871
7. Exposed to crime in question from child/ grandchild	.001648	.000372	.000475
8. Exposed to any crime from child/grandchild	.000020	.000029	.000322
Note: * = not significantly different from zero			

In order to test hypothesis **H3** one needs to compare the AMEs in the relevant adjacent rows of Table 2.4 with one another (1 to 2, 3 to 4, 5 to 6, and 7 to 8). The effects of the exposure variables referring to the *same* type of crime as being analysed provide an indication on how important changes in the specialized crime environment is for the focal individual's likelihood of committing the crime in question. Similarly, the effects of the exposure variables referring to *any* type of crime provides insights into how important changes in the generalized crime environment is for the focal individual's propensity of committing the crime in question.

As can be seen in the first column of Table 2.4, the effects of changes in the specialized crime environment on the focal individual's risk of evading taxes are consistently higher than the effects of corresponding changes in the generalized crime environment. For example, we find that the effect of exposure from close kin on an individual's likelihood of evading taxes is about 6.4 times stronger if the crime committed by the kin was tax evasion rather than some other crime (.000695/.000109).

With the exception for the non-significant effect of bookkeeping crimes among distant kin, one finds the same pattern of exposure effects for bookkeeping crimes as for tax evasion. Changes in the specialized crime environment had much stronger effects on the focal individual's behaviour than did changes in the generalized crime environment. The pattern is the same also for other types of economic crimes, but the magnitude of the differences in the effects are not at all as pronounced as in the case of tax evasion and bookkeeping crimes.

This clearly is not the pattern one would expect to find if the main mechanism at work was norm based because then one would have expected changes in the generalized crime environment to be as important as changes in the specialized environment. I therefore conclude that the data analyses fail to reject hypothesis **H3**. The results seem to suggest that the observed association between crimes of kin and the crime propensity of the focal individual mainly are due to some form of cognition-based learning-mechanism.[30]

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[30] An alternative interpretation should be mentioned although I find it less plausible than the one outlined in the main body of the text. If the relevant normative environments are highly restricted and disjointed from one another, these results could be compatible with the operation of a normative mechanism, because then only kin crimes of the same type would be causally relevant for the focal individual's crime-specific norms and behaviour.

2.5. Concluding remarks

As far as I am aware of, this is the first study of family influences on tax evasion. Research on the role of social interactions in explaining these types of crimes has been seriously hampered by a lack of relevant data. Due to the fact that these crimes are so rarely observed, normal-sized surveys will not be appropriate. In this study I instead used population-level data on all individuals who ever resided in Stockholm County during the years 1990 to 2003.

Although it always is difficult to conclusively identify social-interaction effects (see Manski 2000), the results of these analyses give strong support for the idea that social interactions play a significant role in explaining why some individuals commit these types of crimes. The crime propensity of an individual increases with the proportion of criminal offenders among kin, and the effect of close kin is stronger than that of distant kin. This is exactly the pattern one would expect to find if social interactions had a true causal effect.

It is difficult on the basis of non-experimental data to establish the detailed mechanisms that may have generated these associations between the crime of kin and the crime propensity of the individual. However, some of the findings strongly suggest that cognition-related mechanisms are more likely explanatory contenders than norm-related mechanisms.

As noted in Chapter 1, sociologists rarely study tax evasion. This fact may in part explain why social networks have not been given much attention in the taxation literature. As shown in this chapter, however, it is possible to define, measure, and examine the importance of network influences as long as we have access to large-scale datasets of the kind used here. The results obtained from these analyses are encouraging in the sense that the effect-sizes of the network variables, i.e., kin exposure, were of considerable magnitude. This suggests that taxation research may gain additional insights into the processes at work by adopting a broader sociological approach that pays serious attention to the social environment in which individuals are embedded.

As a final cautionary note it should be observed that the offending individuals are not the sole creators of the kind of data used in this chapter. Since the data refer to individuals who are suspected of having committed various kinds of criminal acts, the behaviour of the law enforcement agencies also matter. This is important since it opens up for alternative interpretations of the results. As argued by Ferraro, Pfeffer, and Sutton (2005) among others, social-science theories can become self-fulfilling when those who design institutions or organizational practices are influenced by the very same theories that later are to be tested with data that in part is generated by these institutions or organizational practices. That is to say, even a theory that initially is incorrect can evoke behaviour and thereby generate data that eventually make the theory appear correct.

A theory thus can find support in empirical data in two principally different ways. First, it can find support because the theory correctly describes the main mechanisms at work in a world that is unaffected by the theory in question. Second, it can find support if the theory influences the behaviour of individuals in such a way that these individuals bring about a world in which the theory is true. MacKenzie et. al. have argued rather convincingly that parts of economic theory is “performative” in this sense of the term (see e.g., MacKenzie 2007), but is there any reason to think that the results reported in this chapter reflect the performativity of network theory?

The analyses presented in this chapter were guided by theories that emphasized the importance of social influence and social embeddedness and the data analyses strongly supported the main hypotheses. Since the data in part is influenced by the behaviour of the law-enforcement agencies, the performativity thesis cannot be dismissed on a priori grounds, however. For example, if the law enforcement agents had read and been influenced by the very same theories of embeddedness and social influence that guided the analyses in this chapter, it seems reasonable to think that they would focus particular attention on the kin of already known offenders. This would in turn mean that crime among kin of criminal offenders would have a higher likelihood of being detected and registered in the data. If this were the case, we would find support for our network-effect hypotheses even if kinship ties to past offenders had no causal influence whatsoever on the behaviour of the individuals.

Although one cannot exclude the possibility that the data and the results of the data analyses in part may reflect these sorts of performativity processes, it seems much more plausible that the results reported here indeed reflect the hypothesized causal effects of the network ties. It is not until the last couple of years that social-network inspired ideas have come to be adopted by Swedish law-enforcement agencies, and then typically only for dealing with organized crime (see Leinfelt and Rostami 2012). Hence, particularly during the time period focused upon in this chapter, network theory simply did not have the influence and recognition among law-enforcement practitioners in Sweden that it would have needed in order to become self-fulfilling.

Chapter 3. Pathways into tax crimes

3.1. Introduction

Many analytical sociologists see Merton's writing on the so-called Matthew effect as an ideal illustration of the type of explanatory mechanisms that they believe the theoretical toolbox of sociology should be composed of (e.g., Hedström and Udéhn 2009; Hedström and Ylikoski 2010). The Matthew effect is used to explain commonly observed polarization processes where those who have many X, tend to get even more X, and those who do Y, tend to do even more Y, whatever X and Y may be. It derives its name from the Gospel According to St Matthew where it is stated:

> For unto every one that hath shall be given, and he shall have abundance: but from him that hath not shall be taken away even that which he hath.[31]

To fully appreciate how the Matthew effect works, consider the following hypothetical example. Assume two doctoral students, **A** and **B**, who are identical to one another in all respects that are relevant for their academic performance. By chance, **A** happens to get a more able and conscientious advisor than **B**, and this random event at the beginning of their graduate

[31] Quoted from Merton (1968a: 58).

studies may come to have a long-lasting impact on their academic careers. The better advise offered to **A** makes **A** produce an excellent doctoral thesis while **B** ends up producing a thesis of more ordinary quality. If **A**'s excellent thesis makes universities and research councils believe that **A** has unusual gifts, this is likely to make them behave in ways that give **A** better opportunities to produce excellent work than **B**. And if **A** manages to capitalize on these opportunities, their initial beliefs will be confirmed and they are likely to offer even more research support to **A**. Merton expressed the core idea of the Matthew effect as follows:

> When the scientific role performance of individuals measures up or conspicuously exceeds the standards of a particular institution or discipline—whether this be a matter of ability or chance—there begins a process of cumulative advantage in which those individuals tend to acquire successively enlarged opportunities for advancing their work (and the rewards that go with it) even further (1988: 616).

At its core, the Matthew effect is a general positive-feedback mechanism that is likely to operate according to a similar logic in a wide array of settings, and it is by far the most well known sociological feedback mechanism of this type. It can be said to operate when individuals who perform an action of type Y, whatever Y may be, alters the beliefs and behaviours of others in such ways that the individuals' likelihood of performing yet more actions of type Y increases. This type of mechanism has been used for explaining phenomena as diverse as socio-economic inequalities (e.g., DiPrete and Eirich 2006) and the evolution of networks

(Barabasi and Bonabeau 2003), and as will be shown below, it also seems important for explaining certain aspects of tax-related crimes.

One important empirical signature that this kind of positive-feedback mechanism leaves in observational data is a strong association between past and present actions of the same kind, and this was exactly what the analyses in Chapter 2 revealed. That is, it was shown that an individual's past criminal record has a considerable impact on the probability of the individual committing a tax-related crime in the present even when controlling for a large number of relevant socio-demographic factors. The positive association between past and future crimes is not unique for this study but is a well-documented empirical regularity. People who commit criminal offenses at one point in time, are more likely than non-offenders to commit crimes at later points in time as well (see Nagin and Paternoster 1991, 2000).

The chapter is organized as follows. In the next section I discuss various positive-feedback mechanisms that seem important for explaining tax behaviour. Thereafter I present the data and the type of statistical models to be estimated. Then the empirical results are presented. First, I examine the crime sequences leading into tax evasion and bookkeeping crimes. Thereafter the results of panel analyses are presented that examine the extent to which the relationship between past and current crimes seems causally genuine or not. The chapter concludes with a summary and discussion of the most important findings.

3.2. *Mechanisms and hypotheses*

As discussed in previous chapters, the general approach adopted in this thesis embraces the analytical-sociology approach with its focus on mechanisms, as well as Granovetter's (1985) embeddedness approach with its view of the actor as a socially embedded individual whose beliefs, norms, values, and opportunities are shaped by the behaviour of those with whom the individual interacts. From this general perspective, if an individual's crime at one point in time is a good predictor of the individual's likelihood of committing another crime at a later point in time, a positive-feedback mechanism with the following structure appears to be a likely causal contender: Crime$_{t1}$ -> Behaviours of others$_{t2}$ -> Probability of Crime$_{t3}$. That is to say, crime breeds crime because if an individual commits a crime, it affects the behaviour of others, and their change in behaviour influences the individual in such a way that his/her probability of offending increases even further. The more precise ways in which this can happen is best explained with reference to a simple decision tree like the one in Figure 3.1.

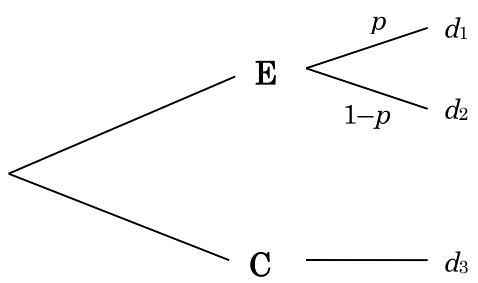

Figure 3.1. Decision tree illustrating the choice between committing a crime (E) and not committing a crime (C).

An outcome-oriented individual deciding whether or not to commit a crime should compare the value of not committing the crime, d_3, with the expected value of committing the crime. The expected value, in turn, is influenced by the probability of not being caught, p, the value of a successful crime, d_1, and the outcome value if the individual is caught for the crime, d_2. More precisely, the individual should commit the crime if $d_3 < pd_1+(1-p)d_2$. Real-life individuals obviously rarely do these kinds of calculations, but the framework nevertheless is valuable since it seems reasonable to think that these decision-making factors are systematically related to the *probability* of committing a crime. That is to say, even if individuals do not base their actions on expected-value calculations, it seems likely that their probability of committing a crime is increasing with increasing values of p, d_1, and d_2, and decreasing with an increasing value of d_3.

Now assume that an individual has been caught for a previous crime, what kind of mechanism could possibly *increase* the individuals' likelihood of choosing the criminal alternative once again? Ideas about deterrence effects would suggest the opposite, i.e., that an individual who has been convicted or suspected for a crime will become less likely to offend again. However, at least two types of mechanisms are likely to work at odds with the deterrence effect; one of them changes the value of the non-criminal alternative, d_3, and the other changes the outcome value if the individual is caught for a second crime, d_2.

The first type of mechanism is rather straightforward: once an individual has been caught for a crime, this tends to reduce the individual's employment prospects (c.f., Thornberry and Christenson 1984; Grogger 1995), i.e., the value of d_3. Everything else being equal, a lowering of d_3 will make the criminal alternative appear more attractive in relative terms, and this will increase the likelihood of the individual committing additional crimes. Thus, this is a kind of positive-feedback mechanism through which crime generates further crimes because the more crimes an individual commits, the worse the individual's employment prospects are likely to become, and this will further increase the individual's probability of offending.

The second type mechanism is somewhat more complex. The relationship between d_1 and d_2 may be thought of as $d_2 = d_1 - v - s$ where v is what the individual can gain from the criminal activity, e.g., the taxes evaded, and s is the sanction imposed on the individual if he/she is caught for the crime, and the relevant sanctions can be formal, f, as well as informal, i. The formal sanctions may include fines and incarceration, and informal sanctions can include peer disapproval, embarrassment, negative reputation effects, social stigma, etc. (c.f., Grasmick and Bursik 1990; Nagin and Paternoster 1994). The decision criteria thus can be restated as follows

$$d_3 < pd_1 + (1-p)(d_1 - v - f - i) \qquad (1)$$

and this brings to the fore that the stronger the formal and informal sanctions are, the less favorable the criminal alternative will be relative to the non-criminal alternative. Since an individual's likelihood of choosing the criminal alternative is likely to be related to the payoff differences between the alternatives, the strength of formal and informal sanctions are likely to influence the likelihood that an individual commits a crime.

While there is no reason to think that the formal sanctions, f, would be lower for second-time offenders than for first-time offenders, this is rather likely to be the case for informal sanctions, i. As suggested by the Dutch proverb "Honor once lost never returns", informal sanctions are likely to be more strongly or even exclusively felt by first-time offenders. That is, once it becomes known that an individual has committed a crime, "honor" is lost and since an honor which already has been lost cannot be lost again, the decision criteria for the second criminal offense becomes $d_3 < pd_1+(1-p)(d_1-v-f)$. Since the right-hand side of this expression is larger than the right-hand side of expression (1), it suggests that an individual who has committed a crime in the past is more likely to commit a crime in the present than an otherwise identical individual who has not committed any crimes in the past. For example, to the extent that social approval, reputation, honor, etc. are important, most individuals without a criminal past are less likely to evade taxes than otherwise identical individuals with a criminal past because members of the latter group already have been classified as criminal offenders by friends and acquaintances and hence have less to lose if apprehended.

Both of these mechanisms, the one that operates via d_3 and the one that operates via d_2, suggest that if an individual is apprehended for or suspected of having committed a crime, this will alter the social situation of the individual in such a way that his/her likelihood of committing further crimes increases. Although expressed in different terms, the mechanism that operates via d_2 resembles some of the core ideas behind labeling theory (e.g., Lemert 1951 and Becker 1963). Labeling theory puts strong emphasis on how individuals' identities are formed in interaction with others and argue that individuals often view themselves through the eyes of others. If others view those who have broken legal rules as "criminals", there is a risk that the rule-breaking individuals themselves will accept and internalize the label, and this may further perpetuate their deviant status. In a similar vain to what was argued above, Becker (1963) emphasized that this makes it difficult for the rule-breaking individuals to return to mainstream life because they tend to be denied access to the means needed for such a life, and this is likely to cement their outsider status. Hence, plausible causal mechanisms exist, supported by various traditions in sociological research that also in the taxation realm may bring about a causal effect of past on future crimes.[32]

3.3. Description of data and statistical models

Since the Stockholm data to be used in this chapter already has been described in detail in Chapter 2 (see pp. 66-69), I will keep this description

[32] Labelling theory also focuses much attention on those persons in power who label certain acts as deviant or criminal. Although this is not a thread picked up on in this thesis, it seems to be a highly relevant focus for additional studies. As emphasized above, the distinction between legal tax avoidance and illegal tax evasion varies in seemingly rather arbitrary ways from country to country and from one time period to another within any given country. These arbitrary differences could have considerable consequences for how the acting individuals are viewed by others and by themselves, however, and thereby have long-term effects on their lives and future careers, criminal as well as non-criminal. While successful tax avoidance often is viewed and described in salutary terms as examples of smart and insightful business strategies, tax evasion typically is viewed as a deviant and immoral act that can have serious consequences for the individual in question.

to a minimum. The analyses include all persons, 16 years or older, who resided in Stockholm County during at least one of the years 1990 to 2003. The chapter focuses on tax evasion and bookkeeping crimes, and examines the extent to which the probability of an individual committing one of those crimes was related to the individual's past criminal history. For some of the analyses I focus on individuals who evaded taxes or committed bookkeeping crimes in 2003 and I examine the criminal sequences that preceded these crimes. In other analyses, I make use of the full data set, and estimate panel models that examine the link between past and future crimes.

The fact that past and current crimes are related to one another does not necessarily mean that past crimes causes current crimes. Using Heckman's (1981) conceptual distinctions, a positive association between past and current crimes can be explained in two principally different ways, as a consequence of *state dependence* or as a consequence of *population heterogeneity*, and the type of mechanisms discussed above are of the former kind. At the core of the state-dependence perspective is the idea that an individual who commits a crime somehow is affected by the criminal act in such a way that his/her propensity to commit further crimes increases. The population-heterogeneity perspective instead is based on the idea that criminal offenders differ from other individuals in terms of their propensity to commit crimes. For example, in Gottfredson and Hirschi's (1990) influential general theory of crime, lack of self-control plays such a role; it is a stable personality trait that differs on the average between offenders and non-offenders. If such a personality trait is excluded from the statistical analysis, it may appear as if past crimes causes current crimes even if that is not the case.

The two perspectives thus differ from one another in terms of the causal role they attribute to past crimes. If the state-dependence perspective is correct, a systematic relationship between past and current crimes reflects the existence of a genuine causal relationship. If the population-heterogeneity perspective is correct, however, a systematic relationship between past and current crimes suggests that a variable measuring a crucial personality trait has been omitted from the analysis. As argued in the previous chapters, while existing research clearly shows on the importance of deep and stable personality factors, particularly when it comes to explaining crimes of passion, it seems much less likely that such factors would play a central role when it comes to explaining white-collar crimes of the kind focused upon here. For these types of emotionally "cold" crimes it appears more essential to focus on cognitive and decision-making mechanisms of the kind discussed above and in previous chapters, while not denying the role that unmeasured personality factors may play.

Schematically the difference between a state-dependence perspective (A) and a pure population heterogeneity perspective (B) is illustrated in Figure 3.2.

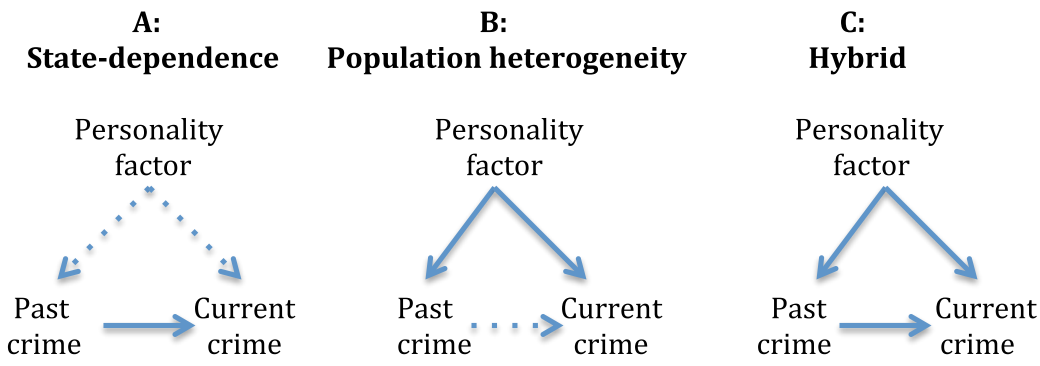

Figure 3.2. Causal paths according to the state-dependence perspective (A), a population heterogeneity perspective (B), and a hybrid perspective (C). Solid lines indicate causal relationship and dotted lines indicate spurious or causally unimportant relationships.

As emphasized by Nagin and Paternoster (1993), although individual researchers tend to emphasize the importance of either the state-dependence or the population-heterogeneity perspective, there is nothing inherently contradictory in the two perspectives. It is difficult to empirically distinguish between the two, but in many situations it seems likely that both operate at the same time, and this is what I refer to as the hybrid perspective (C) in Figure 3.2. If the causal structure looks like (C) but we ignore the personality factor and assume the world to look like in (A), our inferences about the effects of past on current crimes are likely to be upwardly biased. Hence, if both processes are likely to be at work, it is important to control for unobserved heterogeneity even if we are exclusively interested in the state-dependence effects. For this reason, although the empirical analyses reported below seek to test hypotheses of the state-dependence kind, the analysis allows for the world to look like (C), and this is accomplished by estimating panel models that control for unobserved heterogeneity.

Fixed effect and random effect logit models are the most common type of panel models used when the outcome to be analyzed is discrete and when there is reason to suspect unobserved heterogeneity (see Halaby 2004 for a discussion of these types of models). The fixed effect estimator has the advantage of not being based on as strict assumptions as the random-effect estimator is, but it has the major disadvantage of only using data on individuals whose values on the outcome variable change over time. Hence, if the fixed-effect estimator were to be used in these analyses most of the data would be ignored since the estimator only uses data on individuals who committed at least one tax-evasion or bookkeeping crime during the time period being studied. Ignoring most of the data is highly wasteful from a general efficiency point of view, but the selection on the dependent variable that it implies also makes the fixed-effect strategy seem doubtful from a substantive point of view. Since the population of criminal offenders is a highly selected sub-population, it seems doubtful whether estimates based on such a selected population could be generalized to the population at large. For these reasons, random-effect logit models are used since they do not imply a selection on the dependent variable but make use of the data on the entire population.[33]

[33] As expected, preliminary fixed-effect estimates (not shown here) proved to be much less precise than the random-effect estimates, and the fixed-effect estimator also produced some estimates that seemed highly implausible on substantive grounds.

3.4. *Repeat offenders and criminal sequences*

This section seeks to provide a better understanding of the pathways through which crimes in the past are linked to tax evasion and bookkeeping crimes in the current. The analysis focuses on all individuals who committed such crimes in 2003 -- all in all 654 tax evasion and 1,007 bookkeeping offenders were observed during that year. The focus is restricted to crimes taking place in 2003 in order to be able to observe as long pre-history as possible. I follow these individuals back in time and record what crimes they have committed during this time window, if any. Although the approach is largely descriptive, knowing the sequences leading into tax evasion and bookkeeping crimes may help us to better understand the processes at work. As suggested by Tak Wing Chan, "ascertaining how events unfold complements, if it does not have logical priority to, the search for causal factors" (1995: 469). Although left-hand truncation means that some crime sequences will not be fully observed and hence appear shorter than they actually were, there is no reason to expect the left-hand truncation to systematically alter the ordering of the crimes, and it is the ordering of crimes rather than the length of the sequences that is of most concern here.

Table 3.1 shows the twenty-five most common crime sequences leading up to bookkeeping or tax-evasion crimes in 2003. In order to understand the meaning of the sequence identifiers in the table, the following crime codes are needed:

1 = Violent crime

2 = Theft

3 = Drug-related crime

4 = Other non-economic crime

5 = Bookkeeping crime

6 = Tax evasion

7 = Other economic crime

Thus, for example, a Sequence ID of 215 means that the sequence that ended with a bookkeeping offense in 2003 was preceded by a violent crime, which in turn was preceded by a theft.

Table 3.1. The 25 most common crime sequences leading up to bookkeeping and tax evasion offenses in 2003.

BOOKKEEPING SEQUENCES:			**TAX-EVASION SEQUENCES:**		
Sequence ID	**Frequency**	**Per cent**	**Sequence ID**	**Frequency**	**Per cent**
5	397	40	6	259	40
45	71	7	46	41	6
65	37	4	66	28	4
75	33	3	26	22	3
15	27	3	16	20	3
25	25	2	76	15	2
55	20	2	56	14	2
445	14	1	446	10	2
44445	12	1	666	8	1
35	10	1	456	7	1
245	8	1	44446	6	1
755	7	1	146	5	1
115	6	1	466	5	1
665	6	1	166	5	1
41445	5	<1	426	4	1
775	5	<1	766	4	1
455	4	<1	116	3	<1
675	4	<1	1246	3	<1
215	4	<1	36	3	<1
4445	4	<1	1446	3	<1
425	4	<1	4416	3	<1
745	4	<1	266	3	<1
725	4	<1	176	3	<1
645	4	<1	1116	2	<1
4415	3	<1	366	2	<1

The result suggests a great deal of similarity between the bookkeeping and the tax-evasion sequences. The three most common sequences are the same for both types of offenses. The most common sequence is a sequence of one, i.e., that the offending individual had not committed any other crime in the past. Since 40 per cent of the individuals had these one-sequence patterns, it also means that 60 per cent of the individuals who committed these kinds of crimes in 2003 had a past criminal record.

The second most common patterns are sequences 45 and 46, i.e., that the route into bookkeeping and tax-evasion crimes went through a non-economic crime other than a violent crime, a theft, or a drug-related crime. Individuals who followed the third most common sequences, 65 and 66, arrived into their bookkeeping or tax-evasion crimes from a prior tax-evasion crime. Collectively, approximately 50 per cent of the individual sequences followed one of these three patterns.

One important difference between the bookkeeping and the tax-evasion sequences concerns the extent of crime-specific path-dependency. As the table shows, it is almost three times as common that a tax-evasion sequence included a prior tax-evasion offense than a bookkeeping sequence including a prior bookkeeping offense. Close to 12 per cent of the tax-evasion sequences in Table 3.1 contain more than one tax-evasion offense, while only 4 per cent of the bookkeeping sequences contain more than one bookkeeping offense. Since there are many more bookkeeping than tax-evasion cases in the data, the opposite would have been expected by chance.

These descriptive results are interesting and suggestive, but they do not allow us to assess whether the sequences have any consequences for individuals' probability of committing bookkeeping and tax-evasion crimes. In order to establish whether the sequences as such matter, we need to include offenders as well as non-offenders into the analysis, we need to control for other factors likely to be of importance for individuals propensity to commit these types of crimes, and we need to utilize the panel structure of the data in order to control for unobserved heterogeneity.

3.5. Panel-data estimates

As discussed above, random-effect logit models will be used in order to control for unobserved heterogeneity. In addition to covariates describing crimes in the past (if any), the model includes the control variables described in Table 3.2. That is to say, when examining the impact of past crimes on current crimes, we control for gender, age, marital status, education, immigrant status, income, and self-employment. The results of the analyses are found in Table 3.3a (regression coefficients) and Table 3.3b (odds ratios).

Table 3.2. Description of control variables and their hypothesized effects

CONTROL VARIABLE:	**DESCRIPTION:**
Gender	A dummy variable distinguishing between women (=1) and men (=0).
Age	Four dummy variables distinguishing between the following age groups: 18-25, 26-35, 36-65, and 65+.
Single	A dummy variable distinguishing between single (=1) and married/ cohabiting with children (=0).
Education	Three dummy variables based on the individual's highest level of education in a given year distinguishing between low education (less than high school), mid-level education (completed high school), and high education (at least some university education).
Foreign background	A dummy variable that identifies individuals with "foreign background". An individual is considered to have a "foreign background" if both of his/her parents were born outside of Sweden.
Income	Natural logarithm of the total amount of employment and business income earned by the individual during the year in question.
Self employed	A dummy variable that identifies persons who had at least some income from own business during the year in question.

The effect of the control variables can be summarized as follows: gender has a strong negative effect on both types of crime which means that men are much more likely to commit these types of crimes than women are even when controlling for all the other variables included in the model. Whether an individual has a foreign background or not makes no difference, however. Single individuals, on the other hand, are more likely to commit these types of crimes than married individuals are, but the magnitude of the effect is rather modest. Individuals in working age (26-65) are much more likely to commit these types of crimes than those in the youngest (omitted) age group and those in the 65+ group, and this is exactly what one would expect since working-age individuals are likely to have more opportunities to commit these types of offenses. Highly educated individuals, i.e., individuals with at least some college education, are less likely to commit these types of offenses than other comparable individuals are, and the same is true for individuals with high incomes. Finally, the self-employed are much more likely to commit bookkeeping and tax evasion crimes than are comparable individuals who are not self employed – the odds ratios are in the range of 3-4. This strong effect of the self-employment variable most likely reflects the fact that the self-employed have greater opportunities to commit these types of crimes than other individuals have, but it could, of course, also in part reflect a self-selection of individuals with a low tax-morale into self employment.

As far as the effects of past crimes are concerned, these results suggest that individuals who have committed crimes in the past are more likely to commit a tax evasion or bookkeeping offense in the present than are comparable individuals without a criminal record. The effect-sizes are considerable. If an individual has committed a non-economic crime in the past, his/her crime propensity increases with a factor of 2-3 for tax evasion and a factor of 3-5 for bookkeeping offenses, while the corresponding odds ratios are in the range 25-65 for bookkeeping and tax-evasion offenses of the past (see model 1 and 3 in Table 3.3b).

Given the nature of this data, it is not reasonable to interpret the high odds ratios for the economic-crime variables as point estimates of their likely causal effects. Rather, I think they should be seen as upper bounds on the effects, and the odds ratios for the non-economic crime variables should be seen as lower bounds for the effects of the economic crime variables. As discussed in the conclusion of the last chapter, this data is not only a reflection of the behaviour of criminal offenders but is also the result of the behaviour of the law-enforcement agencies. If these agencies were aware of the criminological literature on repeat offending or if they have observed such patterns on their own, it seems highly likely that this would influence their enforcement behaviour. That is, if an individual has been caught for tax evasion in the past, it may influence the behaviour of the law-enforcement authorities in such a way that their future tax returns are scrutinized in more detail. The high odds ratios would then reflect a mixture of the kind of mechanisms discussed above and increased detection risks due to performativity-like processes. Since non-economic crimes are so common, it is less plausible that the behaviour of the tax authorities are influenced by such crimes, and the odds ratios for those variables therefore can be seen as a lower bound on the effect – and this effect still is considerable.[34]

Models 2 and 4 in Table 3.3a and Table 3.3b are the same as models 1 and 3 with the exception that they also estimate the effect of the yet prior crime in the crime sequences. All of these Position 2 crimes have positive and statistically significant effects on the individuals' propensity to commit tax evasion and bookkeeping crimes in the present. The magnitude of the effects are lower than for the corresponding Position 1 crimes, however, and this is particularly true for bookkeeping and tax-evasion offenses. Including these Position 2 crimes in the analysis reduces the estimated effects of the Position 1 crimes, but only with some 15-20 per cent.

[34] One could also consider another process with the reversed time order that could generate these kinds of results: If an individual is detected for a tax crime in the present, the tax authorities are likely to scrutinize his past tax returns in detail as well and this may reveal crimes in the past. A discussion with researchers at BRÅ suggests that such a process is very rare and therefore unlikely to account for any substantive part of these observed effects.

Table 3.3a. Random-effect logit models of tax evasion and bookkeeping offenses. Logistic regression coefficients (Z-values within parentheses). *N*=17138741.

	Tax evasion:	Bookkeeping:		
	(1)	(2)	(3)	(4)
Gender	-1.582	-1.558	-1.436	-1.403
	(-30.82)	(-30.33)	(-29.46)	(-28.71)
Foreign	-.042	-.037	-.005	.008
	(-1.05)	(-.92)	(-.14)	(0.22)
Single	-.060	-.084	.181	.148
	(-1.7)	(-2.39)	(5.30)	(4.32)
Age 26-35	1.590	1.560	1.507	1.459
	(17.11)	(16.78)	(18.66)	(18.08)
Age 36-65	1.799	1.769	1.655	1.606
	(20.22)	(19.88)	(21.51)	(20.87)
Age 65+	.004	.022	-.303	-.288
	(0.03)	(0.14)	(-2.06)	(-1.96)
Mid-education	-.055	-.044	.017	.031
	(-1.31)	(-1.06)	(0.44)	(.82)
High education	-.226	-.202	-.374	-.337
	(-4.65)	(-4.16)	(-7.63)	(-6.87)
Self employed	1.103	1.094	1.405	1.403
	(24.01)	(23.88)	(31.71)	(31.75)
Income	-.048	-.042	-.117	-.109
	(-8.25)	(-7.12)	(-22.26)	(-20.48)
Seq. position 1:				
Violent crime	.981	.785	1.356	1.091
	(12.94)	(9.69)	(21.54)	(15.99)
Theft	1.078	.897	1.310	1.034
	(14.02)	(11.01)	(19.89)	(14.60)
Drug-related	.935	.723	1.460	1.162
	(6.25)	(4.74)	(13.31)	(10.26)
Other non-econ.	1.172	.988	1.623	1.355
	(19.11)	(14.94)	(32.02)	(24.18)
Bookkeeping	4.173	3.862	3.201	3.048
	(47.44)	(42.25)	(23.26)	(20.21)
Tax-evasion	3.509	3.455	3.670	3.231
	(33.11)	(31.27)	(44.31)	(36.26)
Other econ. crimes	2.305	2.097	2.550	2.207
	(34.13)	(29.45)	(42.76)	(34.32)
Constant	-8.511	-8.378	-8.338	-8.196
	(-66.97)	(-64.34)	(-68.45)	(-64.56)
Seq. position 2:				
Violent crime		.323		.412
		(4.08)		(4.98)
Theft		.359		.540
		(3.68)		(6.93)
Drug-related		.520		.492
		(3.15)		(3.55)
Other non-econ.		.523		.632
		(6.45)		(9.32)
Bookkeeping		1.713		1.521
		(10.06)		(7.67)
Tax-evasion		.770		1.286
		(5.14)		(8.90)
Other econ. crimes		.817		1.316
		(8.04)		(16.40)
rho	.249	.184	.228	.154
Log-likelihood	-30164.8	-30083.4	-31807.4	.096

Table 3.3b. Random-effect logit models of tax evasion and bookkeeping offenses. Odds ratios (Z-values within parentheses). *N*=17138741.

	Tax evasion:		Bookkeeping:	
	(1)	(2)	(3)	(4)
Gender	.206	.211	.238	.246
	(-30.82)	(-30.33)	(-29.46)	(-28.71)
Foreign	.959	.964	.995	1.008
	(-1.05)	(-.92)	(-.14)	(0.22)
Single	.942	.919	1.198	1.159
	(-1.7)	(-2.39)	(5.30)	(4.32)
Age 26-35	4.910	4.760	4.514	4.303
	(17.11)	(16.78)	(18.66)	(18.08)
Age 36-65	6.046	5.865	5.236	4.980
	(20.22)	(19.88)	(21.51)	(20.87)
Age 65+	1.004	1.022	.739	.750
	(0.03)	(0.14)	(-2.06)	(-1.96)
Mid-education	.947	.957	1.017	1.032
	(-1.31)	(-1.06)	(0.44)	(.82)
High education	.798	.817	.688	.714
	(-4.65)	(-4.16)	(-7.63)	(-6.87)
Self employed	3.013	2.986	4.074	4.068
	(24.01)	(23.88)	(31.71)	(31.75)
Income	.953	.959	.889	.897
	(-8.25)	(-7.12)	(-22.26)	(-20.48)
Seq. position 1:				
Violent crime	2.668	2.193	3.881	2.977
	(12.94)	(9.69)	(21.54)	(15.99)
Theft	2.938	2.452	3.705	2.812
	(14.02)	(11.01)	(19.89)	(14.60)
Drug-related	2.547	2.062	4.306	3.198
	(6.25)	(4.74)	(13.31)	(10.26)
Other non-econ.	3.231	2.686	5.067	3.877
	(19.11)	(14.94)	(32.02)	(24.18)
Bookkeeping	64.94	47.58	24.57	21.07
	(47.44)	(42.25)	(23.26)	(20.21)
Tax-evasion	33.42	31.65	39.24	25.30
	(33.11)	(31.27)	(44.31)	(36.26)
Other econ. crimes	10.02	8.144	12.80	9.093
	(34.13)	(29.45)	(42.76)	(34.32)
Constant	.00002	.00002	.0002	.0003
	(-66.97)	(-64.34)	(-68.45)	(-64.56)
Seq. position 2:				
Violent crime		1.481		1.510
		(4.08)		(4.98)
Theft		1.432		1.716
		(3.68)		(6.93)
Drug-related		1.682		1.636
		(3.15)		(3.55)
Other non-econ.		1.688		1.881
		(6.45)		(9.32)
Bookkeeping		5.545		4.576
		(10.06)		(7.67)
Tax-evasion		2.159		3.617
		(5.14)		(8.90)
Other econ. crimes		2.264		3.729
		(8.04)		(16.40)
rho	.249	.184	.228	.154
Log-likelihood	-30164.8	-30083.4	-31807.4	-31634.9

In order to assess how the details of the sequences affect the likelihood of individuals' committing these kinds of offenses, Table 3.4 provides more detailed and appropriate information than Table 3.3 since it does not assume that the effects of Position 1 and Position 2 crimes are additive. The two models in Table 3.4 are identical to model 2 and 4 in Table 3.3 but they replace the 7+7 sequence dummies with all 56 one and two position sequences that possibly can be observed. These sequences were defined on the basis of data referring to crimes committed until the end of the year preceding the year during which the outcome variable was recorded. The first seven sequences are single-position sequences, i.e., they refer to situations in which individuals only had committed one offense during the observation window from 1990 to the year preceding the year when the outcome variable was recorded. Thereafter follows 49 two-position sequences representing all possible combinations of the seven types of crimes considered in this chapter, i.e., violent crime (= 1), theft (= 2), drug-related crime (= 3), other non-economic crime (= 4), bookkeeping crime (= 5), tax evasion (= 6), and other economic crime (= 7). The omitted category consists of individuals who had not committed any crimes in the past. Hence, the effect measures in the table, the regression coefficients and the odds ratios, refer to how much higher the propensity of committing the crime is for an individual with a specific sequential pattern as compared to individuals with similar socio-demographic profiles who had not committed any crimes in the past.

Table 3.4. Random-effect logit models of tax evasion and bookkeeping offenses: sequential patterns. N = 17138741.

	TAX EVASION			BOOKKEEPING		
	Coefficient	OR	Z-score	Coefficient	OR	Z-score
Gender	-1.556	.211	-30.28	-1.401	.246	-28.67
Foreign	-.037	.963	-.094	.003	1.003	.09
Single	-.081	.922	-2.31	.151	1.163	4.43
Age 26-35	1.551	4.715	16.68	1.451	4.267	17.97
Age 36-65	1.754	5.777	19.70	1.592	4.914	20.67
Age 65+	.128	1.013	.08	-.297	.743	-2.03
Mid-education	-.041	.960	-1.0	.033	1.033	.86
High education	-.199	.820	-4.11	-.334	.716	-6.82
Self employed	1.086	2.963	23.72	1.393	4.025	31.51
Income	-.042	.959	-7.16	-.109	.897	-20.51
Criminal sequence:						
Sequence 1. (violent crime)	.657	1.929	5.91	.976	2.654	10.35
Sequence 2. (theft)	.823	2.286	7.72	.982	2.670	10.23
Sequence 3. (drug-related)	.888	2.430	4.39	1.193	3.296	7.13
Sequence 4. (other non-econ.)	.820	2.270	9.51	1.250	3.491	17.69
Sequence 5. (bookkeeping)	4.000	54.649	32.39	3.203	24.599	17.13
Sequence 6. (tax-evasion)	3.679	39.605	33.37	3.470	32.128	32.68
Sequence 7. (other econ.)	2.104	8.197	24.05	2.326	10.238	29.97
Sequence 11	1.235	3.440	8.26	1.462	4.315	11.49
Sequence 12	1.330	3.783	4.93	1.563	4.774	7.06
Sequence 13	1.635	5.128	3.97	1.053	2.867	2.10
Sequence 14	1.584	4.873	9.67	1.698	5.461	11.68
Sequence 15	3.945	51.661	12.82	3.456	31.692	10.70
Sequence 16	3.804	44.859	11.77	4.159	63.997	13.47
Sequence 17	1.778	5.916	4.98	2.756	15.740	13.17
Sequence 21	1.281	3.600	5.37	1.794	6.014	10.40
Sequence 22	1.000	2.719	5.55	1.341	3.824	9.74
Sequence 23	.731	2.078	1.46	1.695	5.448	6.05
Sequence 24	1.389	4.010	7.35	1.998	7.375	15.42
Sequence 25	4.520	91.852	16.18	4.081	59.239	14.17
Sequence 26	4.298	73.557	14.43	4.593	98.828	15.43
Sequence 27	2.410	11.139	10.57	2.415	11.193	11.60
Sequence 31	1.201	3.322	2.39	1.588	4.893	4.17
Sequence 32	1.341	3.824	3.26	1.718	5.572	5.64
Sequence 33	.465	1.592	0.80	1.090	2.974	2.86
Sequence 34	1.621	5.058	5.08	1.768	5.860	6.54
Sequence 35	4.615	101.007	8.64	4.399	81.337	8.95
Sequence 36	4.710	111.103	10.08	5.119	167.130	11.37
Sequence 37	2.608	13.572	7.26	2.430	11.364	6.79
Sequence 41	1.277	3.586	6.88	1.775	5.897	12.89
Sequence 42	1.585	4.882	8.52	1.818	6.159	12.00
Sequence 43	.663	1.941	1.32	1.568	4.798	5.38
Sequence 44	1.524	4.592	12.47	1.941	6.967	20.50
Sequence 45	4.408	82.084	20.07	3.614	37.100	13.50
Sequence 46	4.134	62.403	17.25	3.932	51.011	13.98
Sequence 47	2.457	11.668	11.76	2.862	17.502	17.73
Sequence 51	4.582	97.695	11.98	3.555	34.996	7.40
Sequence 52	2.887	17.932	2.84	3.486	32.656	5.72
Sequence 53	5.236	188.062	6.70	5.386	218.338	9.08
Sequence 54	2.912	18.387	4.05	3.670	39.234	8.91
Sequence 55	5.096	163.358	13.86	4.487	88.866	11.56
Sequence 56	4.717	111.846	17.73	4.120	61.570	12.00
Sequence 57	4.685	108.342	11.48	3.607	36.851	6.75
Sequence 61	2.857	17.410	5.47	3.741	42.126	8.87
Sequence 62	2.524	12.476	3.46	3.800	44.683	8.08
Sequence 63	3.202	24.581	4.28	2.915	18.445	2.86
Sequence 64	3.373	29.157	10.19	4.167	64.512	15.71
Sequence 65	5.007	149.401	18.05	4.126	61.914	10.51
Sequence 66	3.726	41.500	15.77	3.505	33.280	12.94
Sequence 67	3.394	29.797	11.55	3.752	42.608	13.35
Sequence 71	1.367	3.934	3.33	2.522	12.456	11.32
Sequence 72	2.436	11.427	10.41	2.537	12.641	12.41
Sequence 73	.686	1.986	.68	3.100	22.199	10.91
Sequence 74	2.264	9.617	10.18	3.003	20.154	20.25
Sequence 75	4.070	58.569	14.37	4.252	70.265	17.66
Sequence 76	3.937	51.272	15.66	4.199	66.639	16.77
Sequence 77	2.999	20.074	19.26	3.298	27.046	25.43
Constant	-8.348	.0002	-64.82	-8.144	.0002	-64.06
rho	.176			.136		
Log-likelihood	-30015			-31561		

The effects of the socio-demographic control variables are very similar to those reported above, but the results for the crime sequences reveal new and interesting information. First it should be noted that the sequence effects are very similar for tax evasion and bookkeeping; the correlation between the bookkeeping and the tax-evasion odds ratios for the 56 crime-sequence included in the analysis is as high as .81. The average odds ratio is slightly higher in the tax evasion than in the bookkeeping model, 35.7 versus 33.2, but overall the effect patterns are very similar.

Comparing the size of the odds ratios for the one-position and the two-position crime sequences reveal that having committed more than one crime in the past substantially increases the risk of committing a bookkeeping or tax-evasion crime in the present. While the average odds ratio for a one-position sequence is 15.9 in the bookkeeping model and 11.3 in the tax-evasion model, the corresponding averages are 37.9 and 35.8 for the two-position sequences. This increase in the odds ratios is particularly strong if a sequence includes a 5 or a 6, i.e., a prior bookkeeping or tax-evasion offense. The average odds ratios for those sequences are 72.4 and 62.5. These strong effects of having prior tax evasion and bookkeeping offenses in the sequences may indicate that some sort of learning-by-doing mechanism is operating that leads some individuals to specialize in certain types of offenses, but as discussed above, they may also be indicative of increased monitoring and detection risks.

The main exception from this pattern is sequences that include a 3, i.e., a drug-related crime. In most cases, such crimes act as a suppressant rather than as a boost. For example, four sequences have effects that are non-significant or of borderline significance, and those sequences all end with a 3, meaning that the individual ended with a drug-related crime. But also in this case, the patterns are complex and not without exceptions. When a drug-related crime is combined with a bookkeeping crime, i.e., sequence 53 and 35, it seems to act as a boost. Of all the sequences that start with a 5, the 53-sequence has by far the highest odds ratio, 188 as compared to an average of 86.2 for the other six two-position sequences that start with a 5. Similarly, the 35-sequence has twice as high odds ratio as the single position 5-sequence has.

It may not be so surprising that having a prior bookkeeping crime in the sequence is more consequential for the probability of committing a bookkeeping crime in the present than having a prior tax-evasion crime in the sequence, but the same is true for tax-evasion crimes in the present. That is to say, having committed prior bookkeeping crimes seem to elevate the risk of committing a tax evasion offense more than having committed a tax-evasion offense in the past. Thus, in the tax-evasion model, the odds ratio for sequence 15 is greater than for sequence 16; the odds ratio for sequence 25 is greater than for sequence 26; the odds ratio for sequence 45 is greater than for sequence 46; the odds ratio for sequence 55 is greater than for sequence 56; the odds ratio for sequence 65 is greater than for sequence 66; and the odds ratio for sequence 75 is greater than for sequence 76. Drug related crimes are the exception once again; sequences 35 and 36 both have very high odds ratios, but the 36 odds ratio is slightly higher than the 35 odds ratio.

Anther important result to note is that the sequential pattern as such often appears to be of considerable importance. That is, the effect of having committed a certain type of offense in the past is not only dependent upon the type of offense but also on where in the sequence it appears. For example, having committed violent crimes and bookkeeping crimes in the past increases the likelihood that an individual will evade taxes in the present, but the increase in the evasion propensity is almost twice as high if the individual first committed the bookkeeping offense – the odds ratio for the 51-sequence is 97.7 while it is 51.7 for the 15-sequence.

One final result to note is the rho-values of the two models, .176 and .136, that measure the extent of intra-class correlation. Although these rho-values suggest that unmeasured personality factors may be of some importance in that they point to the existence of a positive correlation between an individual's propensity to commit a tax-evasion/bookkeeping offense in different years after controlling for the covariates in the model, the intra-class correlations are of rather modest magnitude.

3.6. Concluding remarks.

This chapter has been concerned with the pathways into tax and bookkeeping crimes. For several different reasons, positive-feedback mechanisms are likely to be important for explaining criminal acts like these. For example, when others find out about an individual's criminal behaviour, they may alter their behaviour in such a way that the individual's likelihood of offending increases even further. Thus, individuals who are “rich” in terms of criminal offenses at one point in time are likely to get even “richer” at later points in time.

Prior research has shown that various personality traits such as impulsiveness, myopia, lack of self-control, and aggressive temper also are important for explaining why some individuals and not others commit criminal offenses. Although such factors are likely to be of lesser importance for explaining the types of white-collar crimes focused upon here than for many other types of crimes, statistical models were used that seek to control for such unmeasured heterogeneity.

The results presented in this chapter suggest not only that past crimes genuinely influence the probability of individuals committing crimes in the current; they also suggest that the effects are large compared to the effects of the socio-demographic attributes of the individuals. Furthermore, the results suggest that the order in which past crimes have been committed is important when it comes to explaining an individual’s likelihood of committing a bookkeeping or tax evasion offense in the present. The fact that the sequencing of the crimes appear to be of such importance and that the effects of prior crimes vary so much depending upon the type of crime cast some doubt on the importance of the population-heterogeneity thesis. While it seems perfectly reasonable that deep personality characteristics are important for explaining certain types of criminal behaviour, accounting for the results presented in the chapter with reference to unmeasured personality factors would seem to require the existence of highly crime-specific personality factors, and that seems much less plausible. The strong and differentiated effects of past on current crimes rather suggest the existence of genuine causal effects brought about by positive-feedback mechanisms such as those discussed in section 3.2.

The existence of genuine causal effects of past crimes on current crimes also is important for our understanding of crime dynamics. Strong effects of past on current crimes, such as those observed in this chapter, suggest the existence of an important endogenous positive-feedback component to crime dynamics. Consider, for example, the following sequential progression:

$$0 \Rightarrow 6 \Rightarrow 65 \Rightarrow 655$$

That is to say, an individual starts with a blank crime record and then commits a tax evasion offense. After this first criminal offense, the individual has a single-position crime sequence equal to 6, and as seen in Table 3.4, the odds ratio associated with such a sequence is equal to 39.6. This means that this first step in the criminal career increased the individual's propensity of committing a bookkeeping crime by a factor of 40. If that increase in the propensity resulted in the individual committing a bookkeeping crime, the individual's crime sequence would change to 65. The odds ratio associated with a 65-sequence is even higher than that of a 6-sequence and is equal to 149.4. Thus, the individual's probability of committing a bookkeeping offense takes yet another jump, and in due course the 65-sequence is likely to change to a 655-sequence. Strong endogenous forces thus seem to exist that pull the individual further and further into a criminal career once the first crucial step has been taken. As previously established in Chapters 1 and 2, these initial steps are considerably influenced by another feedback dynamic – social influences emanating from others in the networks in which the individuals are embedded.

In this chapter I have called attention to the potential importance of positive-feedback mechanisms for tax-related crimes. The dynamic interplay between individuals' criminal actions and the reactions of others appears to be of crucial importance for understanding why individuals' commit these types of crimes.[35] Lack of data has meant that it has been difficult to investigate these kinds of processes in the past, but the results presented here suggest that much can be learnt by such a focus.

[35] Strictly speaking, the positive feedback mechanisms focused upon in this chapter cannot explain the first crime in a criminal sequence, but as noted above the vast majority of tax-related crimes are committed by individuals who have committed other crimes in the past.

Chapter 4. Legal tax avoidance: The case of Mexico

4.1. Introduction and hypotheses.

Tax evasion as well as tax avoidance is of considerable importance for tax revenues in Mexico, and they both have significant fiscal and distributional consequences.[36] This chapter focuses on tax avoidance, in part because tax avoidance is important for explaining tax evasion. As discussed in some detail in Chapter 1, although tax avoidance is a perfectly legal activity, it is a crucial activity to understand if we are to understand illegal tax evasion. There are three main reasons for this:

First, as discussed in Chapter 1, there are "causal-leakage mechanisms" that tend to make individuals who engage in legal tax avoidance more prone to also engage in illegal tax evasion. Because the demarcation line between legal and illegal behaviour is not always well defined, tax avoiders often push the boundary for their behaviour in such a way that they eventually often end up evading rather than avoiding taxes. Thus, tax avoidance becomes important for explaining tax evasion because the avoidance dynamics can gradually lead tax avoiders towards tax evasion. This argument is in line with Wikström's and Treiber's work (2009) on the

[36] Mexico is at the bottom of the OECD list in terms of tax receipt with only around 19 per cent of GDP being collected, as compared to almost 35 per cent in EU (see OECD, 2012). For a recent estimation of fiscal evasion and the fiscal cost of 'fraudulent' personal deductions (which can be taken as a proxy for tax avoidance strategies) on corporate taxes, see Barajas et al. (2011).

importance of people’s moral values and moral habits in explaining how they come to be engaged in criminal activities.

Second, tax avoidance practices of *others* are likely to be of importance for explaining an individual’s likelihood of evading taxes. For example, if tax avoidance is frequent, it might affect other individuals’ perceptions about the fairness of the tax system, and thereby make those who feel unfairly treated by the system more likely to evade.

Third, tax avoidance can play a pivotal role as a “host” spreading tax evasion. Since tax evasion is a crime, tax evaders tend to be hidden populations, and there is not much chance for a social contagion process to operate by tax-evaders sharing information with non-tax evaders (unless they are family members, as the empirical evidence shows in Chapter 2). Although tax avoidance also is an activity aimed at reducing one’s taxes, it is legal and therefore not as strongly associated with ‘guilt feelings’ and ‘social stigma’. For this reason, tax avoidance is much more likely to be contagious than tax evasion, and for the reasons discussed above, avoidance often leads to evasion and hence avoidance can function as a host spreading evasion. [37]

Throughout this Chapter I treat claims against tax laws as an indicator of tax avoidance. Let me briefly explain the reasons for this. When firms appeal against tax laws, in almost all cases they seek a reduction or refund of taxes. Thus, claiming against tax laws is a form of legal tax avoidance

[37] The fact that I emphasize the potential importance of tax avoidance for explaining tax evasion does not mean that tax avoidance always leads to tax evasion. As will be shown in Chapter 5, tax avoidance sometimes acts as a substitute for tax evasion.

that many corporations use to minimize their tax liabilities (Mayer-Serra 2009). Therefore, it seems reasonable to use claims as an indicator on the incidence of legal tax avoidance.

In addition to this chapter focusing on legal tax avoidance rather than tax evasion, it differs from previous empirical chapters by focusing on corporate rather than individual actors. The empirical analyses are concerned with testing the following three hypotheses:

- *The resource hypothesis (H1)*: High-income taxpayers (large firms) are more prone to engage in legal tax avoidance than are low income taxpayers (small firms).

- *The positive-feedback hypothesis (H2)*: Having engaged in legal tax avoidance in the past increases the likelihood of engaging in tax avoidance in the future.

- *The social-interaction hypothesis (H3)*: Exposure to legal tax avoidance of others increases the propensity that a taxpayer will engage in legal tax avoidance.

As will be described in more detail below, I use a random sample of all Mexican firms that existed in 2002 to test these hypotheses. This is a unique panel data that never has been analyzed before and which provides a first important test of these hypotheses. Already at the outset I want to emphasize that the data have important shortcomings as well which must be kept in mind when interpreting the results of the analyses. Most importantly, the data set does not contain a great deal of information about the firms and the social and economic environments in which they are embedded. The hypotheses I am interested in testing are of a ceteris paribus nature, i.e., they state what I would expect to observe if I were able to introduce a specific change while holding everything else constant. Even with data that contains a great deal of information on the units of analysis it is difficult to statistically control for all relevant alternative mechanisms (see Morgan and Winship 2007 for a detailed discussion), and with the type of data being used here these problems are pronounced. Hence the results to be reported here merely should be seen as a first rough test of these hypotheses.

The chapter is organized as follows. I start with discussing why corporate tax behaviour matters, and I situate the Mexican case in the international context. After that, I describe the data to be used and the type of statistical models to be estimated. Thereafter I present the empirical results. I present some descriptive statistics and the results of a so-called discrete event-history analysis which seeks to test the three hypotheses listed above. I conclude the chapter with briefly summarizing the results and discussing some of its implications.

4.2. Why corporate tax behaviour matters. Mexico in the international context

Concerns about tax compliance and the costs or loss of revenues arising from tax evasion and legal avoidance are important topics in developing as well as developed countries. Often, international comparisons of tax evasion and tax avoidance focus on individual rather than corporate taxation. The general conclusion seems to be that increasing the corporate tax rates will not lead to increasing tax revenues, and as a consequence of this, corporate taxes tend to be fairly low. Figure 4.1 shows how the average corporate tax rates have developed in OECD countries during the 1981-2010 period.

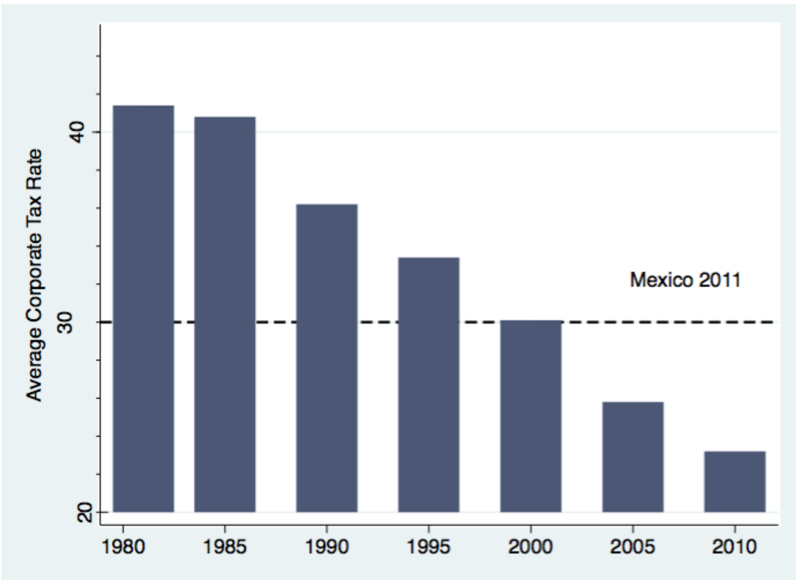

Figure 4.1. Average Corporate Tax Rate for OECD Countries, 1980-2010.[38]

[38] See www.oecd.org/dataoecd/26/56/33717459.xls

As can be seen in Figure 4.1, the average corporate tax rate within the OECD has steadily declined since the 1980s. In 2010 the average tax levy on corporations was around 23 per cent; the lowest ever (despite the fact that OECD has expanded and included some countries with rather high corporate tax rates such as Poland, Turkey, and Greece). For instance, the corporate tax rate in Germany was reduced from 56 per cent in 2004 to 15.8 per cent in 2011; and in the Netherlands it fell from 34.5 per cent in 2004 to 25.5 per cent in 2007.[39]

Table 4.1 shows how the tax rates and tax revenues vary between a large numbers of countries. In addition, the table presents an interesting puzzle: Why do equally developed countries with similar corporate and personal tax structures collect such divergent amounts of income taxes (measured as a proportion of GDP)? Can some of these cross-national differences be due to variations in tax evasion and tax avoidance practices of corporations?[40]

Let us focus on Mexico. As can be seen in Table 4.1, Mexico is at the bottom of the OECD list with a tax receipt of only 19 per cent of GDP (as compared to almost 40 per cent in the EU). This low tax receipt does not appear to be due to nominally lower tax rates in Mexico, however. As can be seen from

[39] See http://www.worldwide-tax.com for current tax corporate rates in most countries.

[40] A set of recent empirical studies have attributed the differences in tax receipts to transfer pricing practices. A transfer price is the price at which goods and services are sold among companies, usually transnational companies. According to Pak and Zdanowikz, in 2000 Canada, Japan, and Mexico, the three most important commercial partners of United States, presented the highest incidence in transfer pricing activities with United States (see Pak and Zdanowicz, 2002, cited on Bartelsman and Beetsma, 2003). Although transfer pricing adds to the explanation, one of the main concerns with this line of analysis is that it may not be convincing that cross-national differences in corporate tax collection can only be attributed to accounting differences, as this literature claims.

Table 4.1, the maximum Mexican corporate tax rate was 30 per cent, which is higher than the EU and OECD average, 23.5 per cent.[41]

In order to get a better understanding of the data presented in Table 4.1, I estimated a linear regression model that included all the countries in the table. The dependent variable was total tax receipt as a percentage of GDP and the model included two independent variables, the highest rate of personal and corporate taxes. Then I used the regression model to make a prediction for Mexico, and this prediction suggests that if Mexico had behaved like the other countries, one would have expected a total tax receipt of approximately 32 per cent as compared to the actually observed value of 19.7 per cent (see Figure 4.2 below).

[41] For some unexplained reason, Mexico did not report the corporate income tax figures in OECD (2012). However, based on an older report (OECD 2006) in which those comparative figures appeared for Mexico we know that in 2004 the corporate tax receipt in Mexico was 1.97 per cent of GDP, compared to the 3.44 average for all OECD countries.

Table 4.1 Tax Structure for OECD Members and Other Western Democracies, 2010

	Total Tax Receipts (% of GDP)	Tax Structures (% of Total Taxation)						Highest Rates of Income Taxes	
		Personal Income Tax	Corporate Income Tax	Social Security Contributions		Taxes on Goods and Services	Other Taxes	Personal Income Tax (%)	Corporate Income tax (%)
				Employees	Employers				
Australia	25.6	38.6	18.5	0.0	0.0	28.4	14.5	47.5	30.0
Austria	42.0	22.5	4.6	14.1	16.2	28.0	8.9	50.0	25.0
Belgium	43.5	28.1	6.2	9.7	19.6	25.6	6.9	53.7	34.0
Canada	31.0	34.9	10.7	6.1	8.7	24.3	13.7	48.0	16.5
Chile	19.6	…	…	6.6	0.3	51.3	3.3	40.0	20.0
Czech Republic	34.2	10.5	9.9	9.1	28.1	33.2	1.3	15.0	19.0
Denmark	47.6	51.0	5.8	2.0	0.1	31.9	4.5	60.2	25.0
Estonia	34.2	15.9	4.0	2.4	35.6	40.2	1.1	21.0	21.0
Finland	42.5	29.7	6.0	6.2	21.1	31.5	2.8	49.0	26.0
France	42.9	17.0	5.0	9.4	26.3	25.0	14.1	50.7	34.4
Germany	36.1	24.5	4.2	17.4	18.7	29.5	2.3	47.5	15.8
Greece	30.9	14.1	7.8	13.2	16.3	39.0	3.2	49.0	20.0
Hungary	37.9	17.1	3.3	9.6	20.2	42.7	5.3	16.0	19.0
Iceland	35.2	36.5	2.7	…	…	35.2	8.7	46.2	20.0
Ireland	27.6	27.0	9.1	7.4	11.6	37.0	6.3	48.0	12.5
Israel	32.4	19.3	9.0	11.8	4.3	40.0	13.5	48.0	24.0
Italy	42.9	27.3	6.6	5.6	21.5	25.9	9.6	48.6	27.5
Japan	27.6	18.6	11.6	18.8	18.6	18.7	10.0	50.0	28.0
Korea	25.1	14.3	13.9	9.5	9.9	33.9	15.0	41.8	22.0
Luxembourg	37.1	21.1	15.5	13.4	12.6	26.9	7.3	41.3	22.1
Mexico	18.8	27.8	…	15.4	…	52.6	4.2	30.0	30.0
Netherlands	38.7	22.3	5.6	15.5	12.8	30.8	4.3	52.0	25.0
New Zealand	31.5	37.7	12.2	0.0	0.0	39.5	6.8	33.0	28.0
Norway	42.9	23.5	23.5	7.4	13.8	27.6	2.9	40.0	28.0
Poland	31.7	14.1	6.3	12.9	14.9	39.4	5.0	32.0	19.0
Portugal	31.3	17.9	9.1	11.3	16.5	39.4	4.6	49.0	27.0
Slovak Republic	28.3	8.1	8.9	11.2	24.3	36.5	1.5	19.0	19.0
Slovenia	37.5	15.1	5.0	20.8	15.5	37.3	1.9	41.0	20.0
Spain	32.3	21.7	5.5	5.9	26.3	26.7	7.0	52.0	30.0
Sweden	45.5	28.0	7.6	5.9	19.0	29.4	9.6	56.6	26.3
Switzerland	28.1	32.3	10.3	11.0	11.0	22.6	7.4	41.7	6.7
Turkey	25.7	14.3	7.4	8.8	13.1	48.4	6.2	35.7	20.0
United Kingdom	34.9	28.8	8.8	7.5	11.0	30.8	12.1	50.0	26.0
United States	24.8	32.8	10.8	11.3	13.0	18.0	12.8	41.9	32.7
EU average	*37.1*	*22.0*	*6.9*	*10.0*	*18.5*	*32.7*	*5.7*	*42.9*	*23.5*
OECD average	*33.8*	*24.0*	*8.6*	*9.6*	*15.0*	*33.2*	*7.0*	*42.5*	*23.5*

Source: OECD (2012)

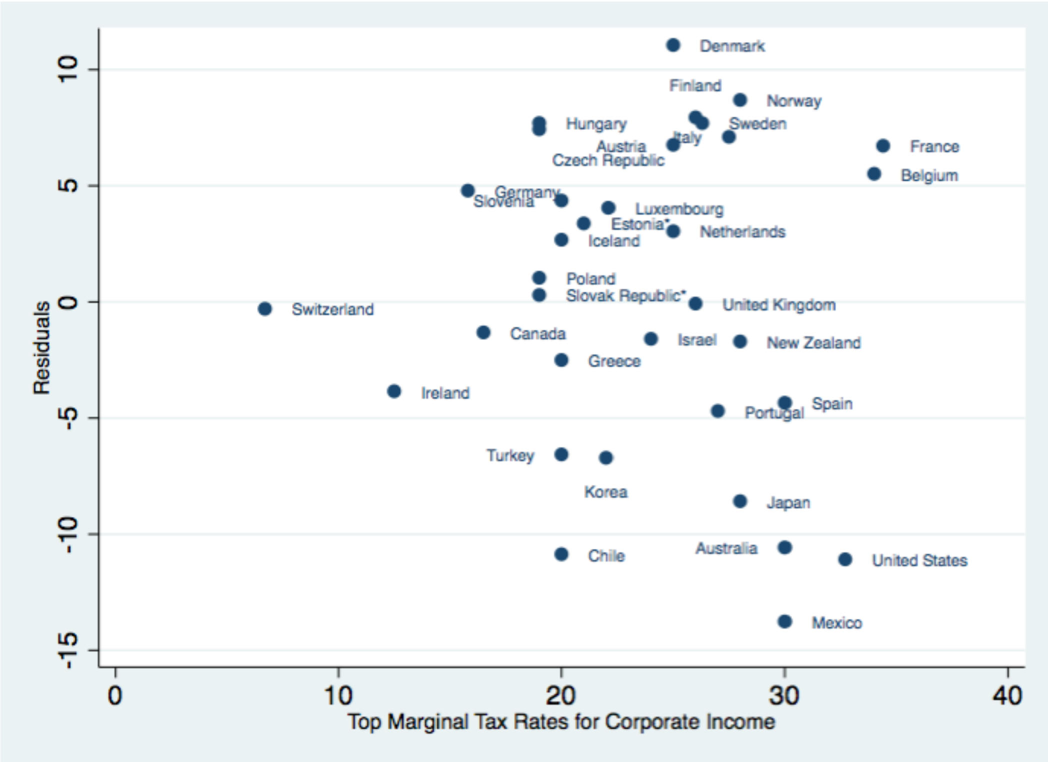

Figure 4.2. Residuals from regression model where tax receipt as a percentage of GDP in 2010 is regressed on the top marginal tax rate for personal and for corporate taxes. [42]

From Figure 4.2 we can see that Mexico is at the bottom in terms of the tax receipt being collected given its personal and corporate tax rates. Although aggregate analyses like this are causally inconclusive, the finding is interesting and may suggest that tax avoidance and evasion are particularly important in the Mexican case (see also Bergman et al. 2005; and Barajas et al. 2011).

[42] It is worth noting that when examining the ratio of tax to GDP, it may be as important to consider the denominator as the numerator. To take a notorious British example, Starbucks in Britain vastly overpays for its coffee ostensibly acquired via Switzerland, thereby reducing its profits. This, however, should reduce the apparent value-added by the British Starbucks operation, and consequently reduce measured British GDP.

We do not know much about the reasons for the large discrepancies that exist between the high nominal tax rates and the low rates actually being paid by corporations. We do not know if most of it is due to tax avoidance or tax evasion. Slemrod (2004) presents empirical evidence on this for the United States, however. Based on a random sample of tax returns filed during the fiscal years 1970 to 1988, the so-called *Tax Compliance Measurement Program* (or TCMP), his results suggest that tax evasion and "abusive avoidance" by corporations indeed might be important explanations. After a fiscal audit had been carried through, a comparison was made between the returns that the corporations were supposed to file and the returns they actually had filed. The TCMP also carried through the same exercise for a random sample of individuals. According to the TCMP, the corporate evasion gap was around 17.4 per cent, whereas the individuals' evasion gap was only about 13.8 per cent. Slemrod also shows that 85 per cent of the corporate evasion gap was due to underreporting of the largest corporations, i.e., companies with over $10 million in assets (p. 3). In view of these results, it seems highly important to try to better understand the role of corporate tax behaviour in explaining why tax receipts are so low in some countries such as Mexico.

4.3. Data and statistical model.

4.3.1. Data

The data to be used in this chapter consists of a random sample of all firms that were in the Federal Register of Taxpayers for the year 2002. This means that the dataset is a random representative sample of all tax paying firms that existed in Mexico in 2002. All in all, 36,949 firms are included in the sample, and these firms are followed until 2008 or until they ceased to exist if that occurred prior to 2008. Thus, the dataset is a firm-level panel.

The data on the legal cases were collected from the records of the Mexican Federal Administrative Fiscal Tribunal in November 2008. It includes all types of claims appealed before them during the 2002-2008 period, and this information was delivered to the Mexican Federal Tax Administration in order for them to merge it with the firm sample.

Table 4.2 describes the total number of firms that remained in the sample year-by-year during the 2002-2008 period. As can be seen, the initial sample size of 36,949 firms decreased rather rapidly during the first few years and thereafter the exit rate fell dramatically.[43] Chapter 5 examines in more detail the likely determinants of these exit rates.

Table 4.2. Number of firms in the sample.

YEAR	**NO. OF FIRMS**
2002	36,949
2003	33,068
2004	31,250
2005	30,507
2006	29,395
2007	29,235
2008	29,232

[43] In comparison with individual-level survey-based panels, the attrition rate is rather low, however.

The variables to be used in the various analyses are described in Table 4.3. The first two variables describe the economic sector and the state within which each firm was located. The former variable distinguishes between nine economic sectors: trade, services, manufacturing, finances, transportation, construction, farming, energy, and mining. The latter variable distinguishes between the 32 states into which Mexico is divided (see Figure 4.5 for details). In some analyses I use a collapsed version of the state variable that identifies the three main regions of Mexico: north, central, and south. The next four variables identifies firms that made 'many' tax deductions, that had more than 1,500 employees, that made a claim during the year, and that won a claim during the year. The variable *Claims among others* measures how common it was that firms similar to the focal firm made claims, and the eighth and final variable identifies whether or not a firm had made any claims in the past (2002 is the beginning of the "past").

Table 4.3. Description of variables to be used in the analyses in Chapter 4 and 5 (means and standard deviations refer to 2002 unless otherwise noted).

VARIABLE NAME	DESCRIPTION	MEAN	STANDARD DEVIATION
Economic sector	A set of dummy variables that distinguish between nine different economic sectors.	--	--
State	A set of dummy variables that distinguish between the 32 different states into which Mexico is divided.	--	--
Many tax deductions	This is an indicator variable that identifies those firms that utilized more than 75% of available types of tax deductions.[44]	0.292	0.455
Large firm	This is an indicator variable that identifies those firms that had more than 1,500 employees.	0.017	0.128
Claim	This variable indicates whether or not a firm made a "claim" during the calendar year in question. A "claim" is defined as a legal procedure through which a taxpayer (corporation] goes before court to appeal against a tax regulation.	0.006	0.076
Winner	This is an indicator variable that identifies firms that won a legal claim during the year in question. The mean is equal to .371 and the standard deviation is equal to .483 among the firms that made a claim.	0.030	0.170
Claims among others	This variable measures the per cent claimants among other firms that are located in the same state and engaged in the same type of economic activity as the focal firm.	2.108	1.653
Previous claims	This is an indicator variable identifying those firms which have had at least one claim during the period from 2002 to the previous year. For the firms that made a claim, the mean is equal to .181 and the standard deviation is equal to .385 during the year in question.	0.009	0.096

4.3.2. Statistical model

The type of statistical model to be used for testing the three hypotheses listed above is a so-called discrete time event-history model (see Allison 1982). This is a regular binary logistic regression model but it is estimated with data which first have been arranged in such a way that each firm

[44] During these years, the Mexican tax legislation allowed only for a fixed number of deductions divided into 4 different types. If a firm used at least 3 out of these 4 types they received the value 1 on this variable, irrespectively of whether the amounts deducted were small or large.

contributes as many observations as the number of years it has been at risk of experiencing the event in question.

Once the data have been rearranged in this fashion, the parameters of a logistic regression model like this can be estimated:

$$\ln\left(\frac{p_{it}}{1-p_{it}}\right) = a + b_1 MT_i + b_2 LF_i$$

where p_{it} equals the hazard or the probability that firm i will make a claim in year t given that it was at risk of making a claim at this point in time, MT_i is a variable indicating whether or not the firm used many tax deductions, LF_i is a variable indicating whether firm i is large or not, and a, b_1, and b_2 are parameters to be estimated (the models actually being estimated also include time-varying independent variables). The logistic command in *Stata 12* has been used for estimating the parameters of the model.[45]

In section 4.4.2 these parameters estimates are reported. The variables used are those referred to in Table 4.3 as *Large firm*, *Claims among others*, *Previous claims*, and *Many tax deductions*, and the dependent outcome variable is the one called *Claim*. I include *Large firm* to test the resource hypothesis (*H1*), *Previous claims* and *Many tax deductions* to test the positive-feedback hypothesis (*H2*), and *Claims among others* to test the social-interaction hypothesis (*H3*). All independent variables are lagged one year so that the hazard of making a claim in year t is assumed to depend

[45] A small number of firms made claims during more than one calendar year. In the analyses reported in section 4.4.2, these cases are included as separate spells (but the standard errors are corrected for this). Whether these cases are included or not makes no difference for the main results, however.

upon the values of the independent variables during year *t*-1. In addition to these variables, I also include annual time dummies in order to allow the baseline hazard to vary over time due to the influence of other factors than those actually being measured and included as independent variables in the model.

4.4. Results.

The analyses reported here focus on tax claims, i.e., on cases in which firms go before court to appeal against tax regulations. The description of the results is divided into three sub sections. I start with presenting some descriptive statistics on the prevalence of claims among firms within different economic sectors, states, and regions. Then I present the results of the event-history analysis, and I conclude with a brief discussion of these results.

4.4.1. Descriptive statistics

Figure 4.3 shows how the proportion of firms making claims varied over time and between different economic sectors. Two aspects are particularly noteworthy. First, the prevalence of claims declined over time, and, second, it varied considerably between different sectors. In fact, this type of tax avoidance was almost entirely concentrated to four economic sectors: finance, construction, energy, and mining. While in these four sectors in between 20 and 50 per cent of the firms made claims in 2002, claim making was of negligible importance in all the other sectors. The data does not allow for any analyses seeking to disentangle why it was so high in these four sectors, but given the types of fiscal reforms that were introduced during these years, it seems reasonable to think that the patterns at least partly can be explained by those changes in the tax code.

For instance, during the period of analysis, 2002-2008, several fiscal reforms affected the financial sector. Numerous reforms, ranging from taxes on cash deposits in trust accounts, taxes on deposits for payments to cover insurance fees, to exemptions for transactions linked to concentration accounts on the pension system, seemed to have had an impact on the accountability of deductions and profitable gains.[46] Therefore, the observed pattern in Figure 4.3 may also in part be due to that firms in the financial sector were more likely to actively work within the grey areas of the new tax legislation. This is important because firms in the financial sector were more prone to challenge the tax authorities' interpretation of the law by bringing cases before not only the Federal Administrative Fiscal Tribunal but also the Supreme Court, and thereby hoping for positive resolutions that could cancel tax liabilities. If this is true, it could signify, first, that firms outside the financial sector are less likely to constitutionally challenge income tax and asset tax legislations, and, second, that financial corporations are more likely to legally avoid tax liabilities and not just those regarding income tax and asset tax legislations. Nevertheless, what is particularly important given the purpose of this thesis is that the introduction of fiscal privileges based on the economic activity of a firm may have important effects on the taxation system and it seems important for

[46] See the different fiscal resolutions (and the corresponding modifications) published in Mexico by the Taxation Authorities during the period 2002-2008.

understanding the spread of legal tax avoidance behaviour among Mexican firms.

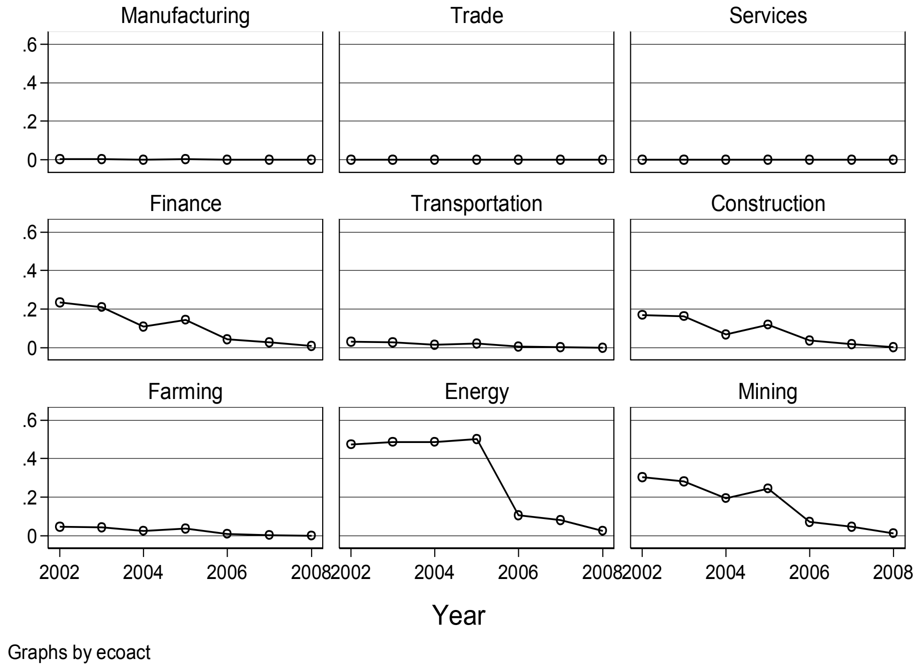

Figure 4.3. Prevalence of claimants in different economic sectors, 2002-2008.[47]

As seen in Figure 4.4, the prevalence of claims varied considerably between southern, central, and northern Mexico, and Figure 4.5 gives more detailed information on how it varied between different states.

[47] There are also several possible data-related reasons as to why Figure 4.3 shows zero or close to zero claimants in some sectors like manufacturing, trade, and services. First, when merging the different databases some claimant firms may have been lost. The merging variable used was the name of the firm and this may have produced some missing cases if the names did not perfectly match (due to misspellings or changes in the name of the firm). Another relevant fact to take into consideration is that claimant firms refer to firms whose cases were closed by 2008. If firms had cases before the Fiscal Tribunal that were still open, those firms were not included. For this reason, the closer we get to 2008, the more likely it is that a firm was not registered as claimant.

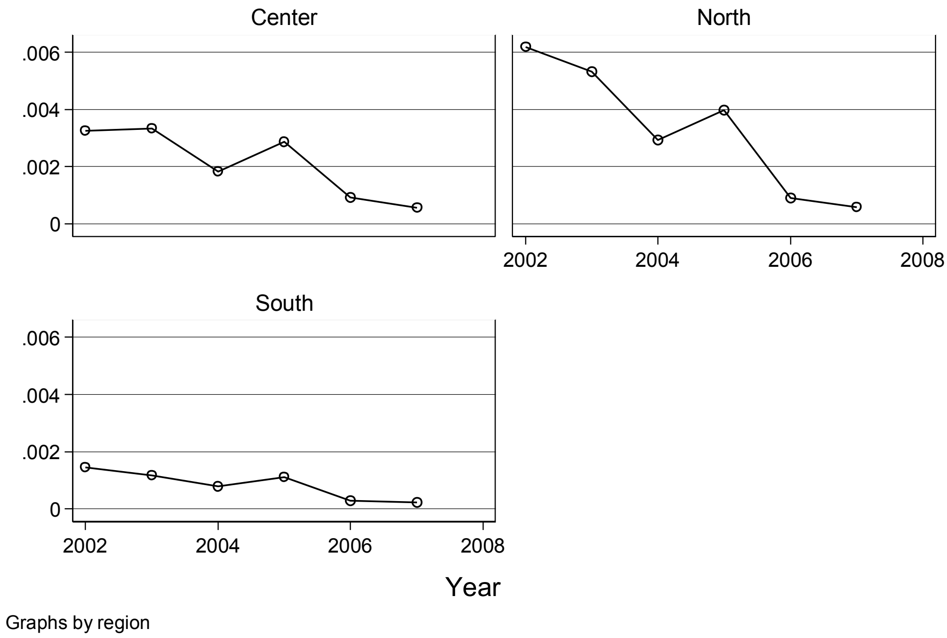

Figure 4.4. Prevalence of claims in different regions, 2002-2008.

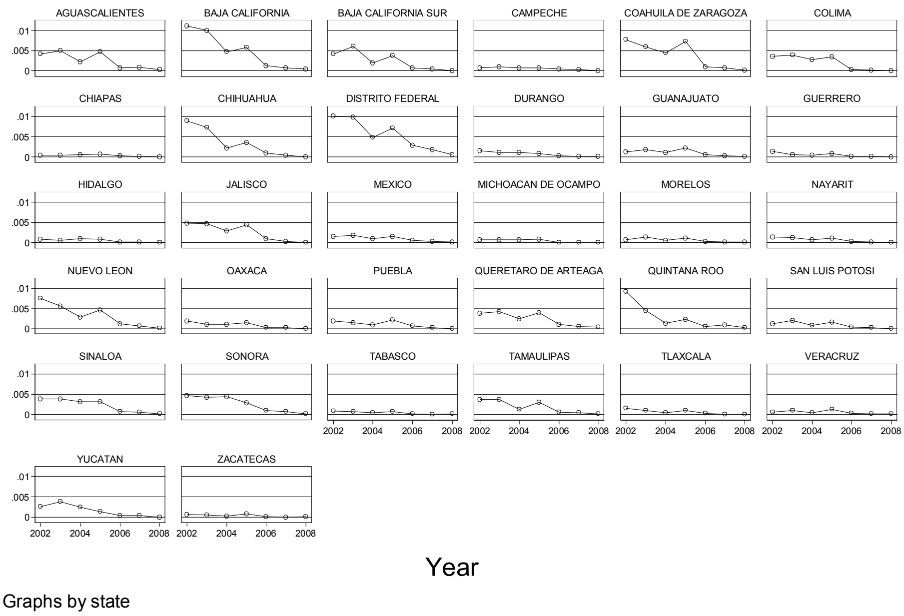

Figure 4.5. Prevalence of claims in different states, 2002-2008.

During the beginning of the period, tax claims were considerably more common in the north than in the south, and the centre region fell in between these two extremes. As far as the southern region is concerned, it should be kept in mind that this is a poor region in which more than 50 per cent of the inhabitants live under the poverty line (Cortez et al. 2002). One plausible explanation for the low prevalence of claims in this region is that most individuals and firms lack the resources needed to mount successful court cases. As Figure 4.5 shows, the only southern state with a high claim rate is Quintana Roo and this is the most prosperous of the southern states. According to the socio-economic marginalization measure of CONAPO (2010), the marginalization rate in Quintana Roo is classified as "low" whereas it is classified as "high" or "very high" in all the other southern states (the higher the level of marginalization, the less access to socio-economic resources the population has).

These spatial variations obviously also reflect variations in the type of economic activities that dominate in different states/regions. In order to shed light on this, Figure 4.6 shows the relative size of the high-claiming sectors in different states in 2003. Firms in finance, construction, energy, and mining are considered as part of the "high claiming" sector.

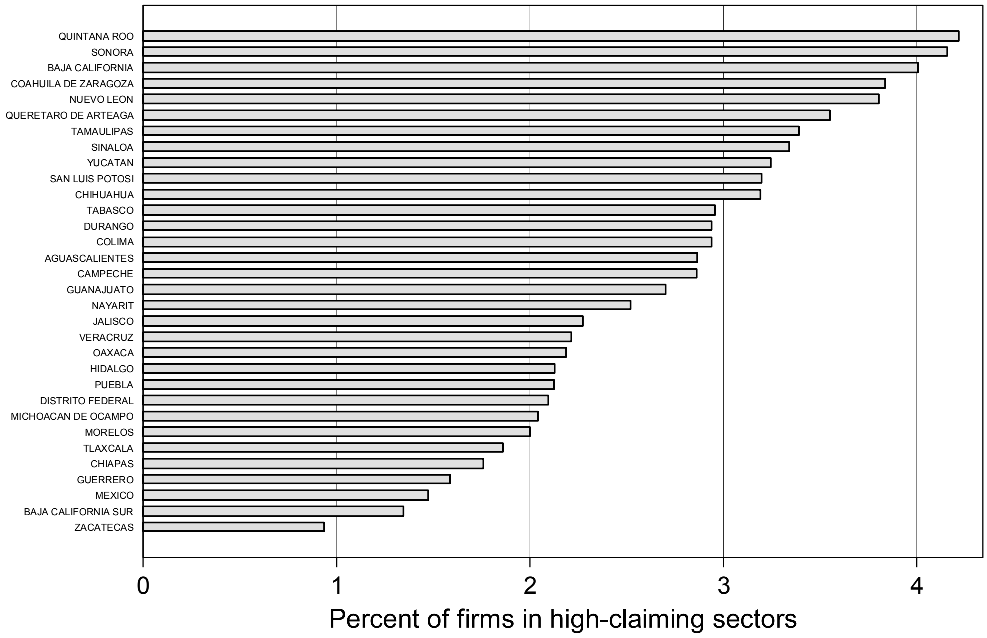

Figure 4.6. Relative size of the high-claiming sector in different states in 2003.

Although the finance sector is larger in the north and farming is more dominant in the south than in the other two regions, the regional differences do not simply reflect differences in the economic activities of its firms. The dataset does not contain enough information to dig deeper into the likely causes of these regional differences. Nevertheless, although somewhat speculative, the results appear consistent with the idea that these differences in part are due to regional differences in social norms. In small sectors such as mining, energy, construction, and farming, uniform norms are more likely to be established because of the greater ease by which behaviour can be monitored and enforced, and small activity-sectors are more prevalent in states with a high incidence of claiming as shown in

Figure 4.6 for the states of Quintana Roo, Baja California, Coahuila, and Nuevo Leon.[48]

4.4.2. Event-history analysis

The result of the event-history analysis is shown in Table 4.4. The parameter estimates for the variables testing the three core hypotheses are shown in the table. In addition, a total of 16 dummy variables are included to control for calendar year, region, and type of economic activity. Since the parameter estimates associated with these dummy variables are of no intrinsic interest in and of themselves they have been excluded from the table. The coefficient column shows how the logarithm of the odds changes with a one-unit change in the independent variable in question, and the odds ratio column shows the proportional change in the odds resulting from a one-unit change in the independent variable.[49]

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[48] Obviously it is not only the case that regional differences are partly explained by differences in economic activities; the differences we observe between firms engaged in different types of activities in part also is likely to be due to differences in their geographical locations. Although highly interesting, to disentangle the mutual relationship between economic activities, on the one hand, and geographic locations, on the other, fall outside the scope for this thesis.

[49] I also tried several alternative specifications of the model, including the random effect model. Although the size of the parameter estimates of course changed slightly from one specification to another, qualitatively the results were the same and did not change any of the substantive conclusions. For this reason I report the estimates of the standard discrete-time event history model recommended by Allison (1982).

Table 4.4. Testing claim-related hypotheses. Parameter estimates of event-history model (N = 189,361).

VARIABLE	COEFFICIENT	ODDS RATIO	Z-VALUE
Large firm	0.272	1.312	1.94
Many tax deductions	0.213	1.237	4.13
Previous claims	3.862	47.540	52.13
Claims among others	0.030	1.031	2.46
Constant	-5.449	--	-42.02
-2LLR: 3004.48			
Note: The robust sandwich estimator of variance has been used, and the standard errors are corrected to allow for intra-group correlation between observations of the same firm at different points in time. Note: Dummy variables to control for calendar year, economic activity, and region also are included.			

The *Large firm* variable is included in order to test the resource hypothesis (*H1*). The coefficient has the expected positive sign and the odds ratio suggests that the odds of making a claim is about 31 per cent higher among large than among small firms when controlling for the other variables included in the model. The Z-statistic suggests that the significance of the effect is a borderline case, however. In approximately 52 samples out of 1,000 one would find a coefficient this large or larger even if firm size and the propensity to claim were unrelated to one another in the population at large.

The *Many tax deductions* and *Previous claims* variables have been included to test the positive-feedback hypothesis (*H2*), i.e., the idea that if a firm has been engaged in legal tax avoidance in the past, in and of it self this is likely to increase the probability of the firm engaging in tax avoidance also in the present (see Chapter 3 for a discussion of the relevant literature in regards to this sort of positive-feedback). Both coefficients have the expected positive signs and they both are highly significant. The odds ratios suggest that the odds of a claim was about 24 per cent higher among firms that had made *many* tax deductions in the past than among those that had not, and that the odds was close to 48 times higher if a firm had made a claim in the past than if it had not. This offers support for the positive-feedback hypothesis, but it should be observed that the effect of the *Previous claims* variable is likely to pick up the effect of other variables influencing the propensity to make a claim, previously as well as currently, which are not included in the model.

The *Claims among others* variable is used to test the social-interaction hypothesis (*H3*), i.e., that exposure to the tax avoidance of others will increase the propensity of a firm to engage in tax avoidance (see Chapter 2 for a discussion of some of the relevant social-interaction literature). The distribution of this variable is shown in Figure 4.7.

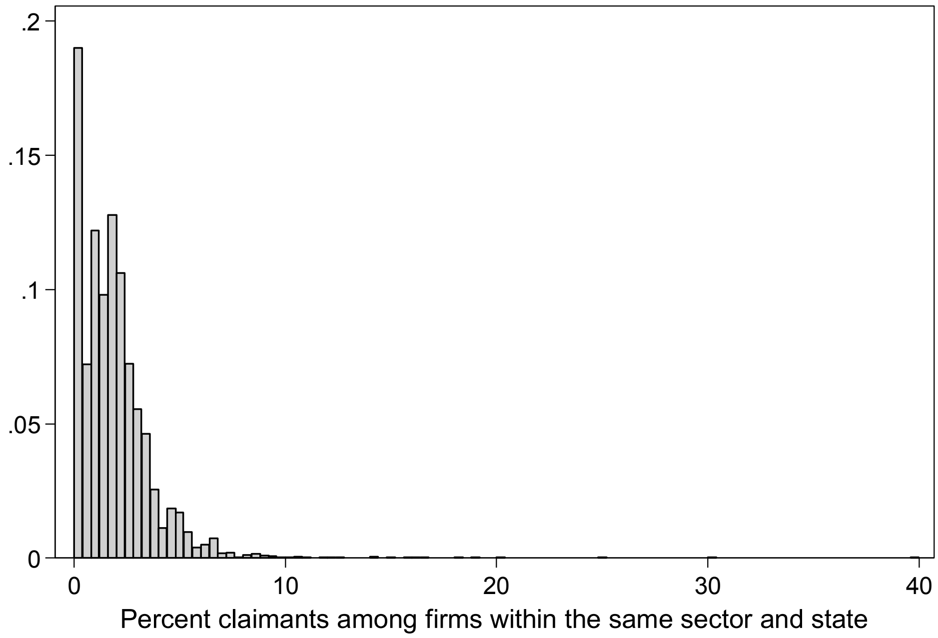

Figure 4.7. The prevalence of claims among other firms within the same sector and state.

During this time period, a considerable proportion of the firms, 17.7 per cent, found themselves in a situation where they had no other claiming firms in their specific combination of economic sector and state. Among the remaining 82.3 per cent of the firms, the percentage varied from a low 0.3 to a high 40, and the average was equal to 2.27 per cent.

If we then return to the results of the event-history analysis, the coefficient associated with this variable is significant and it has the expected positive sign. The odds ratio suggests that a one percentage unit increase in claimants among firms in the same state and economic sector as the focal firm increases the odds of the focal firm claiming with approximately 3 per cent. The results thus support the social-interaction hypothesis.[50]

As far as the social-interaction effect is concerned, one legitimate question is the following: Since the claimants are firms and successful claims represent competitive advantages, why should we expect that firms in the same state and economic sector learn about the successful claimant strategies used by others? Like other competition-enhancing strategies, one would expect firms to carefully guard such secrets. Although this argument carries some weight, there are at least three reasons for nevertheless expecting social-interaction effects to be important. First, information about these legal cases become public as soon as the trial is over which means that a firm can go to the court and learn about the grounds for a claim made by another firm even if the latter firm would have preferred the information to be confidential. Second, many firms are partly or fully owned by the same family and information of this kind is likely to be transmitted within families because doing so does not represent any conflict of interest and norms related to family loyalty may further encourage such behaviour (and this also finds some support in the empirical analysis of Chapter 2 where tax crime data from Sweden was used). Third, many firms use the same lawyers and these lawyers are likely to serve as "super spreaders" who inform some clients about the successful claimant strategies used by other clients.

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[50] In analyses not reported here I also included the square of the claims-among-others variable to test for possible curvilinear effects, but the squared term was not significant.

As Table 4.5 shows, a considerable proportion of companies in all economic sectors used the same tax lawyers or law firms in cases brought before the Supreme Court in 2004. In this table, a firm is classified as using the same lawyer/law firm as others if it uses the same lawyer/law firm name as at least 10 other firms in the same economic sector do. In the economy as whole, 42 per cent of the firms were part of lawyer-mediated clusters, and the percentages were considerably higher in sectors such as manufacturing (79 per cent), construction (63 per cent), and finance (53 per cent). Particularly in these latter economic sectors one could expect lawyers to play an important role in transmitting information from one firm to another.

Table 4.5. Distribution of firms using the same law firms for fiscal trials brought before the Supreme Court in 2004

	FIRMS SHARING THE SAME TAX LAWYERS (%)		
Economic Sector	**Individual lawyer**	**Law Firm**	**Total**
Transportation	0.6	12.4	13.0
Farming	3.8	12.5	16.3
Bank, financial, insurance and rental services	1.7	51.2	52.9
Construction	8.6	54.2	62.8
Energy, gas, and water	13.2	36.7	49.9
Manufacture Industry	21.2	57.8	79.0
Mining	17.9	29.4	47.3
Services	3.4	41.3	44.7
Trade	4.7	14.5	19.2
All economic activities	8.19	33.81	42.0

Source: Own analysis based on data from the *Mexican Federal Administrative Fiscal Tribunal.*

The odds ratios in Table 4.4 tell us how the odds of making a claim is likely to change with a one-unit change in an independent variable (holding the other variables constant). As can be seen from the last column of Table 4.6

(see below), the standard deviations of these independent variables vary considerably, however. For some of the variables we are fairly likely to observe a one-unit change, while for others this is extremely unlikely. To get a better sense of the relative importance of these variables for the propensity to make a claim, one should compare changes in odds resulting from typical variations in the independent variables rather than unit-changes, and the standard deviations can be used for this purpose. Table 4.6 shows the predicted changes in the odds resulting from a standard deviation change in each independent variable.

Table 4.6. Percentage change in the odds of claiming resulting from a standard deviation change in the independent variable.

VARIABLE	**CHANGE IN ODDS**	**STANDARD DEVIATION**
Large firm	3.5%	0.128
Many tax deductions	9.4%	0.424
Previous claims	26.1%	0.060
Claims among others	5.4%	1.719

If we use the proportional change in the odds resulting from a standard deviation change as a measure of relative importance, Table 4.6 suggests that positive-feedback processes are most important for the odds of claiming followed by social-interaction processes and resource-based causes. As mentioned above, the data set does not contain a great deal of information about the firms and the social and economic environments in which they are embedded. Hence the results reported here merely should be seen a first rough test of the hypotheses.

4.5. Discussion

The fact that the decision-makers are different from the owners of the firms has important implications for tax evasion in general, and for the prevalence of legal tax avoidance practices in particular. In corporate behaviour the threat of punishment is not directly assessed and felt by the owners, and managers are expected to behave in a more risk-neutral manner. Tax planning becomes a matter of creative compliance under which companies will have their lawyers actively working on the grey areas of the law (McBarnet 2003). This view of firms' tax behaviour corresponds well with our finding in regards to the resource hypothesis and the differences in the dynamics occurring within activity-sectors. A plausible mechanism already discussed in this chapter implies that firms with more resources will hire better lawyers and so will devote more resources to actively seeking out alternative interpretations of the law.[51]

Ethical questions are not likely to be of as much explanatory importance for tax avoidance behaviour as they are for tax evasion, and this is likely to be true irrespectively of whether the taxpayer is an individual or a corporation

[51] This perspective on corporate tax behaviour differs from that of Slemrod (2004). Slemrod assumes that how far corporations will seek new interpretations of law depends on their corporate 'willingness' to do so. Although he does not seem to dismiss the importance of economic resources, he does not mention them as important determinants of a more aggressive legal tax behaviour.

(Frey and Holler 1998; Hanlon, Mills, and Slemrod 2007). Corporations are more likely to engage in legal tax avoidance, however, because not taking advantages of a legal opportunity to avoid taxes might be seen as a bad management. The support found for the positive-feedback hypothesis is in line with the theoretical discussion in Chapter 1 and suggests that learning-by-doing processes are important for tax-behaviour dynamics. Some of the results reported in this chapter also help to illustrate the effect that social interactions may have on legal tax avoidance of firms in different economic environments.

In concluding this chapter, let me emphasize once again the provisional nature of the findings reported here. Some of the results are interesting and suggestive, but to firmly test the hypotheses requires richer data than what has been available for this study.

Chapter 5. Exit from the legal arena

5.1. *Introduction and hypotheses.*

One important theme in this thesis has been that legal tax avoidance and illegal tax evasion are intimately linked with one another, and that the former may play a pivotal role in explaining the latter. Another important theme has been that of social interactions, i.e., the notion that taxpayers are influenced by the behaviour of other taxpayers. As primarily discussed in Chapter 1, this influence can take place in at least three different ways. First, actors can learn about successful tax-avoidance and tax-evasion strategies from others. Second, actions are influenced by the local normative climate in which the actors are embedded, and the normative climate is dependent upon what others do, i.e., the normative pressure to pay one's taxes is weakened if there is a high prevalence of either tax evasion or tax avoidance in the individual's environment. Third, the probability that a tax evader is detected is likely to be lower the more tax evaders there are (assuming that the authorities' resources for monitoring tax evasion is fixed), and a lower detection probability is likely to make some actors more prone to engage in tax evasion.

In this chapter I focus on one particular type of tax evasion: a firm's decision to leave the legal arena. Disappearing from the white economy is an evasion strategy observed in many countries, but as suggested by

Mironov (2008) and Barajas et al. (2011), it might be a particularly common evasion strategy in Russia and Mexico where tax authorities have not been able to audit activities in which firms use apocryphal documentation to evade considerable sums of taxes.

Mironov's work argues that Russian firms look to reduce their tax liabilities by multiple evasion practices using apocryphal documentation, with relatively big firms being the most prone to move between the black and the white economies. The tax mechanism operates the following way: first there exist shell companies, so called *Spacemen,* and those companies are responsible for simulating the sale of services to 'formally legal' firms. *Formal* firms will pay to *Spacemen* firms by hiring a service that actually does not take place. Then, the *Spacemen* will issue the corresponding invoices for which they will receive a small fee paid by the *Formal* firms. The *Spacemen* then return in cash to the *Formal* firms the amount of the payment made by the service covered on the bill (the fee *Spacemen* usually charge is about 3 or 4 per cent the total amount of the bill). According to Mironov's work, *Spacemen* are relatively big firms within the economic sector and have a very short life, lasting since first appearance usually less than two years.[52]

Barajas et al.'s (2011) work shows how common tax evasion using apocryphal documents is in Mexico. The data the authors use refer to firms that are suspected of conducting operations with apocryphal fiscal documents. The study covers the period from 2007 to 2009 and it started in

[52] Moreover, these firms are more prone to have very high incomes compared to the average of similar firms and they tend to pay very little in taxes, usually less than 0.1 per cent of taxable income. See Barajas et al. (2011: 39-40).

2007 because it was not until then that the taxation authorities in Mexico (SAT) started to systematically check for these types of irregular transactions through the so called DIOT statements (Declaración Informativa de Operaciones con Terceros, in Spanish).[53] The Mexican schemes operated in similar ways to those described in Mironov's work, i.e., firms used formal invoices to overestimate their supply purchases and thereby they reduced their taxable profits and the income tax that they had to pay. This way the firms are committing tax evasion on corporate income tax but also on VAT declarations since they declare a much lower VAT than what they should have done.[54]

For these reasons, this chapter is particularly interested in examining how the disappearance of Mexican firms from the legal arena is influenced by the evasion climate in which the firms are embedded and by their own history of tax avoidance behaviour. The two primary hypotheses that will be tested are the following:

H1: Exposure to the tax evasion of others increases the exit risk.

H2: Firms that have engaged in legal tax avoidance in the past are more likely to disappear.

These two hypotheses are closely related to the social-interaction and positive-feedback hypotheses tested in previous chapters. In addition to these two hypotheses, the following hypothesis also will be tested:

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[53] The DIOTs contain information about the companies' operations with third parties.

[54] For a thorough explanation on these avoidance/evasion schemes, see Barajas et al. (2011: 39-40).

H3: Firms that lose a tax trial are more likely to exit.

The rationale behind *H3* is that losing a legal case of the kind analyzed in Chapter 4 means that the claimant firm has lost the possibility of reducing its tax liabilities. As discussed in Chapter 1, when the legal means of reducing ones taxes is blocked, one can expect firms to start exploring other options. One option and in certain circumstances perhaps the only option of achieving the same result is to enter the black market. And for this reason one can expect that losing a tax trial will increase the likelihood of the firm entering the black market.[55]

As I will return to below, even if the tax avoidance of others affects the likelihood of a firm entering the black economy in order to avoid paying taxes, as emphasized in *H1*, the direction of the influence is somewhat ambiguous because one can expect *substitution effects* as well as *reinforcement effects*. For example, assume that we have two tax evasion strategies, *A* and *B*. If *A* is prevalent in a particular environment it suggests that tax evaders can get away with evading taxes by following strategy *A*. If *A* and *B* are substitutes for one another, there is no reason to expect that the prevalence of *A* will increase the prevalence of *B* in that environment. Rather one should expect that the success of *A* will encourage those using strategy *B* to switch to *A*. In contrast to this, a reinforcement effect would imply that an increase in the prevalence of *A* leads to an increase in the prevalence of *B*. One situation in which one would expect this to happen is

[55] As will be discussed in more detail below, obviously there are other reasons as well to expect an association between losing a tax trial and the disappearance of the firm. For example, winning the legal case may be the last chance for a firm to avoid bankruptcy and once the legal battle is lost the firm has to cease its activities.

if the prevalence of *A* lowers not only the normative pressure against engaging in *A* but also against engaging in *B*.

Before presenting the type of models to be estimated, let me once again emphasize, just as I did in Chapter 4, that the hypotheses to be tested here are of a ceteris paribus nature, i.e., they state what I would expect to observe if I were able to introduce a specific change while holding everything else constant. Even if I had access to a dataset with detailed information on the firms and their local environments it would be difficult to statistically control for all relevant alternative mechanisms, and with the type of data being used here these problems are pronounced. Hence the results to be reported here merely should be seen as a first rough test of these hypotheses. Having said this, some of the analyses presented below are nevertheless novel and generate interesting and suggestive results.

5.2. Data and statistical model.

The data to be used in this chapter is the same sample of Mexican firms as was used in Chapter 4. That is to say, a random representative sample of all tax paying firms that existed in Mexico in 2002. All in all, 36,949 firms are included in the sample.

The outcome event of interest is whether or not a firm disappeared from the Federal Register of Taxpayers during the 2002 to 2008 period. I am interested in whether the probability of this event taking place is related to the firms own tax avoidance history and the extent of tax evasion taking place in the firm's environment.

The dataset does not include any direct measures of tax evasion. As an indicator of the tax-evasion environment I therefore use aggregate statistics on the extent of tax evasion in different economic sectors. These aggregate statistics derive from Barajas et al.'s study (2011), and Figure 5.1 shows how prevalent tax evasion was in different economic sectors.

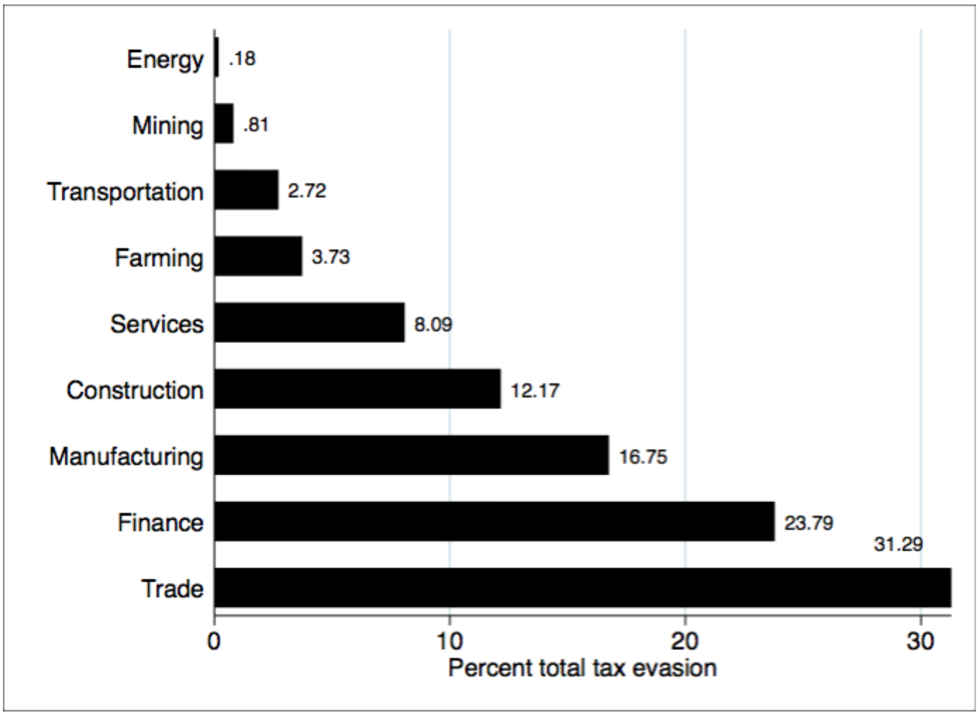

Figure 5.1. Extent of tax evasion among firms in different economic sectors, 2007 (Barajas et al., 2011)

As can be seen in Figure 5.1, most tax-evading firms were in the trade and financial sectors, and the fewest tax-evading firms are found in the energy sector. Since the sectors vary in size we need to control for the size of the sector (see Figure 5.2). The most evasion prone sector then appears to be the financial sector followed by the trade and construction sectors. Evasion was prevalent also in the farming and manufacturing sectors.

Comparing the tax-evasion levels in Figure 5.2 with the tax-avoidance levels in the same economic sectors (see Figure 4.3), one finds interesting differences. Although these data are too aggregated to allow for any causal inferences, the far from perfect fit between evasion and avoidance levels may indicate that tax evasion and tax avoidance act as substitutes for one another. That is to say, the result may suggest that firms are less likely to evade taxes when they have ample opportunities to reduce their taxes via legal means. More detailed analyses are needed to firmly establish if and under which conditions this is likely to hold true, however.

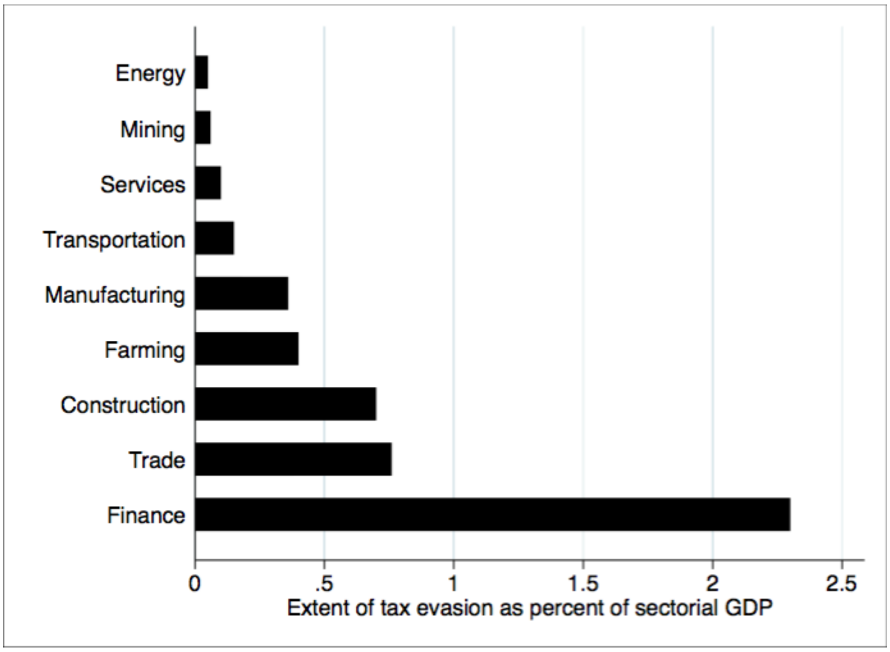

Figure 5.2. Extent of tax evasion within different economic sectors as proportion of sectorial GDP, 2007

In addition to the contextual variable shown in Figure 5.2, I will include the following four independent variables in the analysis:[56]

- *Claim*: This variable indicates whether or not a firm made a "claim" during the calendar year in question. A "claim" is defined as a legal procedure through which a taxpayer (firm] goes before court to appeal against a tax regulation.
- *Large firm*: This is an indicator variable that identifies those firms that had more than 1,500 employees.
- *Winner*: This is an indicator variable that identifies firms that won a legal claim during the year in question.
- *Many tax deductions*: This is an indicator variable that identifies those firms that utilized more than 75 per cent of the available types of tax deductions.

The data to be analyzed has a hierarchical structure. At the lowest level we have information about the firms, and this data has been arranged like a cross-section where each firm has one record. The dependent variable is an indicator variable that identifies those firms that disappeared from the tax records sometime during the 2002 to 2008 period. At the next hierarchical level we have the economic sectors within which the firms are nested, and the sector variable of interest is the evasion variable described above (Figure 5.2).

More formally, the model to be estimated is a two-level hierarchical model. The Level 1 model looks like this:

[56] See Table 4.3 on chapter 4 for a description of the means and standard deviations of these variables.

$\text{Prob}(DISAPPEAR_{ij}=1|\beta_j) = \phi_{ij}$

$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$

$\eta_{ij} = \beta_{0j} + \beta_{1j}*(Claim_{ij}) + \beta_{2j}*(LargeFirm_{ij}) + \beta_{3j}*(Winner_{ij}) + \beta_{4j}*(ManyTaxDeductions_{ij})$

ϕ_{ij} is the probability that firm *i* in sector *j* disappeared from the tax records during the 2002 to 2008 period. The claim variable indicates whether or not the firm had made any legal claims against the tax code during this period, the firm-size variable indicates whether the firm was a large firm in 2002 (i.e., had more than 1,500 employees), the winner variable whether the firm won any tax trials during this period, and the deduction variable identifies those firms which in 2002 utilized more than 75% of the available types of tax deductions.

The model is a regular logistic regression model with one important exception; the regression coefficients are allowed to vary between the nine economic sectors referred to above (see Figure 5.2), and the regression coefficients are assumed to be a function of the extent of tax evasion in each sector. The Level 2 model to be estimated looks like this:

$\beta_{0j} = \gamma_{00} + \gamma_{01}*(Evasion_j) + u_{0j}$

$\beta_{1j} = \gamma_{10} + \gamma_{11}*(Evasion_j)$

$\beta_{2j} = \gamma_{20} + \gamma_{21}*(Evasion_j)$

$\beta_{3j} = \gamma_{30} + \gamma_{31}*(Evasion_j)$

$\beta_{4j} = \gamma_{40} + \gamma_{41}*(Evasion_j)$

That is to say, each Level 1 regression coefficient is assumed to be a linear function of the evasion level in the sector, and in the case of the intercept of the Level 1 equation we also assume the existence of a random effect (u_{0j}). The software being used to estimate the parameters of the models is *HLM 7*.

5.3. Results.

5.3.1. Descriptive statistics

Figure 5.3 shows how the risk of disappearing changed over time for this sample of firms. The risk is defined as the number of firms which disappeared between year t and t+1, divided with the number of firms that existed at year t.

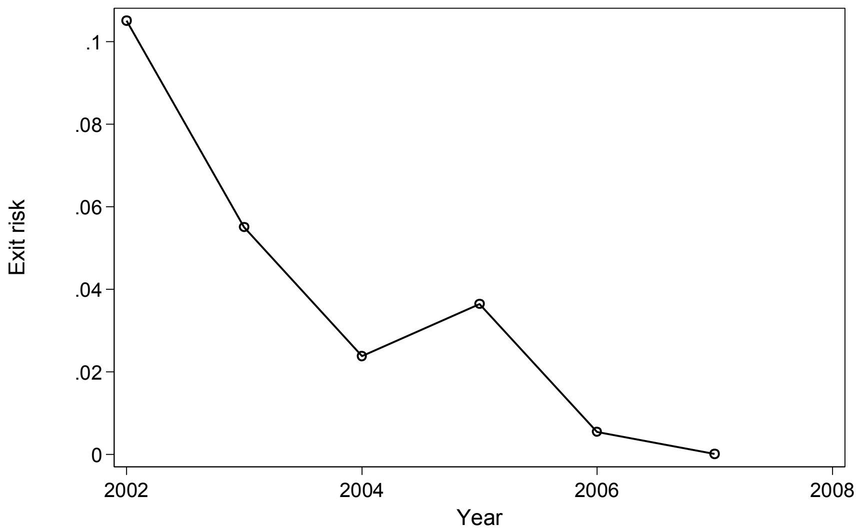

Figure 5.3. Changes in risk of firms disappearing.

As can be seen in the figure, the risk initially is high but falls rather dramatically during the first two years. The pattern may in part reflect so-called “liability of newness”, i.e., the tendency of new firms to experience a greater risk of failure than older organizations (Stinchcombe 1965; Freeman, Carroll, and Hannan 1983). That is to say, the 2002 firm sample may have included many newly founded firms. Many of them disappeared during the following two years, and those that survived were a selected sub-population that was better adapted to the environment and therefore less likely to disappear. In addition, and of more interest to this thesis, as Mironov (2008) and Barajas et al. (2011) have argued, this pattern could also be explained by the so-called “Spacemen’ firms that although relatively large, their only purpose of existence is to make available tax evasion opportunities to others but they have to end their activities rather quickly so that the tax authorities cannot keep track of them. Since the dataset does not include any information about the age of the organizations, it is not possible to say whether liability of newness or illegal activities indeed are the reasons for the observed pattern.

5.3.2. Multi-level analysis.

As mentioned above, the hypotheses are tested with a multi-level logistic regression model. The parameter estimates are found in Table 5.1. The first two parameters, γ_{00} and γ_{01}, refer to the intercept of the Level 1 model. The γ_{00}-value of -1.587 suggests that the probability of a firm disappearing is approximately equal to 0.169 when all explanatory variables at both hierarchical levels are equal to zero.[57] That is to say, these results suggest

[57] $e^{-1.587}/(1+e^{-1.587}) = 0.169$

that a “small” firm that did not make any claims, that did not make much use of the available tax deductions, and that was embedded in an evasion-free environment had 0.169 probability of disappearing.

Table 5.1. Parameter estimates of multi-level logistic regression model.

LEVEL 1 VARIABLE	**MODEL PARAMETER**	**PARAMETER ESTIMATE**	**T-RATIO**
Intercept	γ_{00}	-1.587	-62.521
Intercept	γ_{01}	-0.012	-0.443
Claim	γ_{10}	1.335	19.626
Claim	γ_{11}	-0.192	-2.418
Large firm	γ_{20}	-0.109	-0.746
Large firm	γ_{21}	-0.014	-0.091
Winner	γ_{30}	-1.140	-9.256
Winner	γ_{31}	0.263	1.808
Many tax deductions	γ_{40}	-0.059	-1.495
Many tax deductions	γ_{41}	-0.005	-0.127
Note: The data upon which the model is estimated refers to 36,307 firms and 9 economic sectors. Restricted maximum likelihood is the estimation technique being used.			

The γ_{01}-value of -0.012 is not significantly different from zero (the t-value is equal to -0.443 which suggests that in 67 out of 100 samples would one observe a γ_{01}-value this size or greater even if the true population value was equal to zero). Hence, the results suggest that the extent of tax evasion in the economic sector is unrelated to the probability of a firm disappearing, and this suggests that hypothesis *H1* should be rejected. The negative sign of the parameter estimate may possibly suggest a tendency towards a substitution effect, i.e., that when one type of tax evasion is frequently adopted, the likelihood of observing other types of evasion strategies is reduced.

The next two parameters, γ_{10} and γ_{11}, refer to the claim variable. The γ_{10}-value of 1.335 and the associated t-value of 19.626 suggest that a firm that has made a claim is significantly more likely to disappear than is a firm that did not. Although there exist many possible reasons for observing this relationship, taken at face value and if interpreted in terms of the concerns of this thesis, it offers some evidence in support of a reinforcement effect between these forms of tax avoidance and tax evasion (as will be observed below, however, the effect also depends on the outcome of the claim—whether the firms wins or loses the trial).

The γ_{11}-value of -0.1929 and the associated t-value of -2.418 suggest that the effect of having made a claim on the probability of disappearing is lower in high-evasion than in low-evasion sectors. The relationship between the three types of strategies thus is rather complex and can be illustrated as in Figure 5.4.

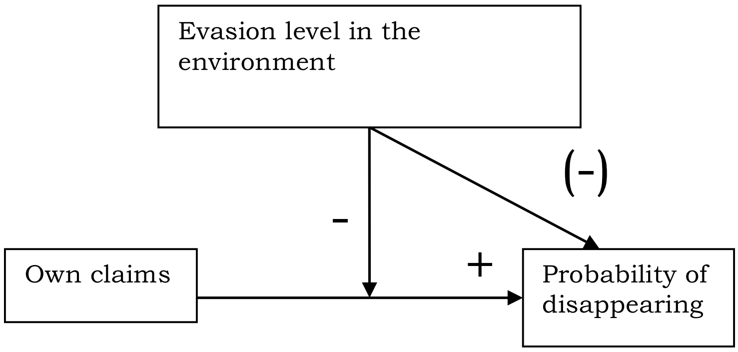

Figure 5.4. Partial relationships between three types of tax avoidance and tax evasion behaviour.

As Figure 5.4 seeks to illustrate, there is a reinforcement effect between claiming and disappearing, and there is a tendency towards a substitution effect between evasion and disappearing. In addition to this, there is an interaction effect, which is such that the extent of evasion in the environment moderates the reinforcement effect that exists between claiming and disappearing.

Another potential explanation for this result is that firms under financial pressure are more likely to make claims and also more likely to disappear. Unfortunately the data does not allow me to distinguish between these two alternative explanations. Both processes are likely to be at work, but since making legal claims are costly, I do not think the latter process is the dominating one because “dying” firms are not likely to be able to afford such trials.

The next two parameters, γ_{20} and γ_{21}, refer to the firm-size variable but neither of them are statistically significant. The following two parameters, γ_{30} and γ_{31}, which refer to the outcome of the claim are significant, however, and they are substantively interesting. The γ_{30}-value of -1.140 suggests that a firm that won a legal claim is less likely to disappear than other firms, and the γ_{31}-value of 0.263 suggests that this negative effect is more pronounced in sectors with low tax evasion (this latter effect only is a tendency, however, since the t-value is 1.808). Since the variables *LargeFirm* and *ManyTaxDeduction* are not statistically significant, Table 5.2 presents the multilevel-model re-estimated without those two variables.

Table 5.2. Parameter estimates of multi-level logistic regression model (without the variables *LargeFirm* and *ManyTaxDeduction).*

LEVEL 1 VARIABLE	**MODEL PARAMETER**	**PARAMETER ESTIMATE**	**T-RATIO**
Intercept	γ_{00}	-1.606	-70.878
Intercept	γ_{01}	-0.013	-0.543
Claim	γ_{10}	1.335	19.619
Claim	γ_{11}	-0.193	-2.429
Winner	γ_{20}	-1.141	-9.264
Winner	γ_{21}	0.263	1.811
Note: The data upon which the model is estimated refers to 36,307 firms and 9 economic sectors. Restricted maximum likelihood is the estimation technique being used.			

Once again, the results are rather complex, particularly considering the fact that the effect of the claim variable is positive and that its interaction with the evasion level is negative. For this reason, Figure 5.5 shows graphically what these partial effects imply.

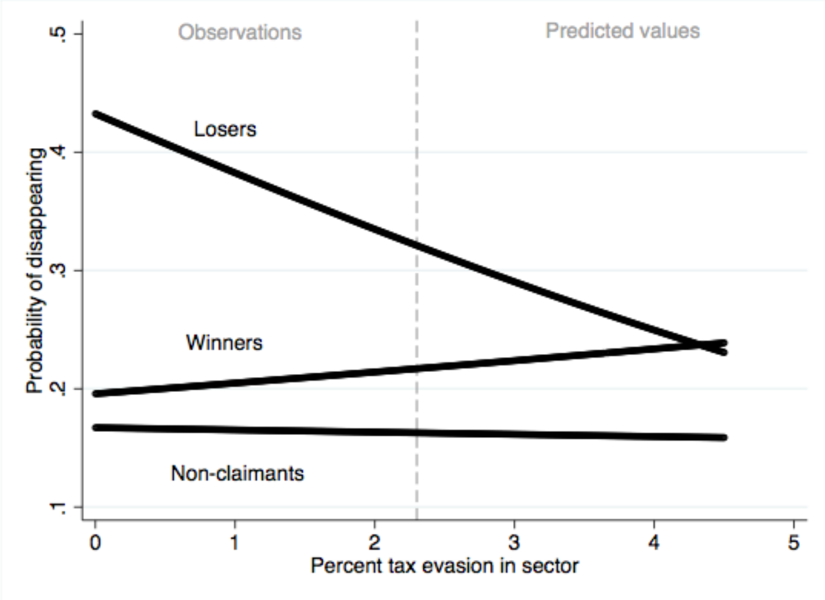

Figure 5.5. Relationship between evasion level in the economic sector and the probability of a firm disappearing for firms that have won a trial, lost a trial, and not been involved in a trial respectively.[58]

This figure is based on the parameter estimates of Table 5.2 and shows that firms that made a claim but lost the trial are most likely to disappear. Firms that brought a case to trial and won are much less likely to disappear, but least likely to disappear are the firms that never made any claim. These results offer strong support for hypotheses *H2* and *H3*. The figure also shows that differences between firms in the evasion levels of the environments in which they are embedded, as well as differences in their own tax-avoidance history are of considerable importance for their probabilities of disappearing.

[58] Figure 5.5 is based upon the following equation:

$$\ln\left(\frac{p_{ij}}{1-p_{ij}}\right) = -1.606 - 0.013 \bullet Evasion_j + 1.335 \bullet Claim_{ij} - 0.193 \bullet Evasion_j \bullet Claim_{ij}$$
$$-1.14 \bullet Winner_{ij} + 0.263 \bullet Evasion_j \bullet Winner_{ij} + u_{00}$$

5.3.3. Event-history model. A second approach.

Table 5.3 reports the estimates of a discrete time event history model that tests the same hypotheses as the HLM model did but which makes proper use of the time dimension of the data. The outcome variable is equal to 1 if the firm disappeared in that year and zero otherwise. The environmental disappearance rate is measured as the proportion of firms in the same state and economic sector as the focal firm that disappeared during the year. All independent variables have been lagged one year.

Table 5.3. Parameter estimates of an event-history model examining the determinants of firms disappearing from the governmental tax records (N = 220,098).

VARIABLE	**COEFFICIENT**	**ODDS RATIO**	**Z-VALUE**
Large firm (*t*-1)	-0.099	0.905	-0.88
Many tax deductions (*t*-1)	-5.918	0.003	-19.41
Claim (*t*-1)	0.807	2.242	16.51
Winner (*t*-1)	-.708	0.493	-7.62
Environmental disappearance rate (*t*-1)	3.919	50.351	16.84
Constant	-2.411	--	-57.61
-2LLR: 2220.22			
Note: The robust sandwich estimator of variance has been used, and the standard errors are corrected to allow for intra-group correlation between observations of the same firm at different points in time. Dummy variables to control for calendar year also are included.			

Qualitatively, the results reported in Table 5.3 are very similar to those reported in Table 5.1 with two important exceptions.[59] First, according to these estimates, firms that utilized many tax deductions during the previous year were significantly less likely to disappear from the tax records. Taken at face value this result does not support hypothesis *H*2 but suggests that there is a substitution effect between these sorts of tax avoidance and tax evasion strategies. A more plausible interpretation, however, may be that firms that used many tax deductions fared better in the competition with other firms and for this reason they were less likely to disappear. Second, the lagged value of the variable measuring the disappearance rate in the same combination of state and economic sector as the focal firm had a strong positive effect on the probability of the firm disappearing from the tax records. Taken at face value this result offers strong support for the social interaction hypothesis (*H*1) and suggests that firms which observe other firms using this evasion strategy are more likely to adopt this strategy themselves. But obviously there are many other plausible explanations for this finding that rather has to do with this variable picking up effects of other unmeasured factors that are shared by the firms in the same state and sector.

5.4. Discussion.

The empirical analyses presented in this chapter have sought to relate tax avoidance and tax evasion to one another. As in the previous chapter, the tax avoidance variables are tax claims and the use of many tax deductions.

[59] If the evasion variable used in Table 5.1 is included as an independent variable in the model reported in Table 5.3, it is statistically insignificant and has a point estimate close to zero.

Since the dataset does not include any direct measures for tax evasion I used aggregate statistics on the extent of tax evasion in different economic sectors. Since disappearance from the white economy is a well-established evasion strategy, I used disappearing from the legal arena as a proxy for tax evasion. The analyses concentrated almost entirely on social interaction effects and positive-feedback mechanisms.

Exit from the legal arena is perhaps the most extreme form of tax evasion. Our findings for Mexico suggest that legal avoiders, whose opportunities for reducing their tax liabilities are blocked (i.e., those who lost a trial), are considerably more likely to exit the white market than those who successfully reduce their tax burden by legal tax avoidance practices. An interesting result of this chapter is that firms that avoid taxes are also more likely to evade taxes, but as tax evasion becomes more prevalent in the environment, legal tax avoidance (claims against the tax code) becomes less important. This may indicate that in high-evasion environments taxpayers do not find any use in trying to reduce their tax burden through legal means.

The highly aggregate data on tax evasion that I have examined makes it difficult to generalize these results to other contexts and countries, however. More disaggregate data on tax evasion, as well as information about the firms and the social and economic environments in which they are embedded is needed. Hence the results reported here merely should be seen a first rough test of the hypotheses.

Text

Chapter 6. Concluding remarks: On the role of positive feedback in explaining tax behaviour

In this brief concluding chapter I will highlight some of the recurrent themes of previous chapters and discuss some of their implications. One of the core themes has been analytical sociology and its explanatory approach. But since I already have discussed that approach in detail in Chapter 1, I will instead focus this concluding discussion on the type of *positive-feedback mechanisms* that all the chapters have been concerned with. The *feedback* aspect of the mechanisms means that the past is causally important for the current, and the *positive* aspect of the mechanisms means that the events of the past make events in the current more likely. Expressed somewhat differently, what this class of mechanisms has in common is the following causal pattern: If individual j did X at time t, individual i is more likely to do X and time $t+1$, and we can distinguish between two types of such mechanisms:

1. an interaction-based type of mechanism where $j \neq i$, and
2. an intra-actor type of mechanism where $j = i$.

In Chapter 1 I discussed various mechanisms of this kind, and I focused particular attention on the first type of interaction-based mechanism where the tax behaviour of others is an important part of the explanation for the tax behaviour of the focal individual. For example, many experiments have shown that most people are conditional altruists who contribute to public goods as long as they know or believe that others are doing the same (Gintis et al. 2005; see Fehr and Gintis 2007). If a conditional altruist believes that others are paying the taxes they are supposed to pay, they are likely to do the same even if they would be better off economically by not doing so. But if conditional altruists believe that others are not paying their taxes, neither will they. The fact that a conditional altruist is so sensitive to the behaviour of others means that social-contagion processes are likely to be important for explaining variations in tax behaviour. The agent-based simulations suggested that social-influence processes similar to these can be of considerable importance for the macro-level evasion patterns that emerge.

In Chapter 2 I examined in detail the empirical support for the first type of positive-feedback mechanism using data on tax evaders and other economic offenders in Stockholm County. The focus was on kinship relations and the data analyses gave strong support for the idea that social interactions play a significant role in explaining why some individuals commit tax crimes. The analyses showed that the crime propensity of an individual increased when exposed to criminal kin, and the effect of close kin was stronger than that of distant kin. This is exactly the pattern one would expect to find if the first type of positive-feedback mechanism was in operation.

In Chapter 3 the emphasis turned to the second type of positive-feedback mechanism, i.e., the intra-actor kind of mechanism. The chapter was concerned with positive-feedback mechanisms linking a specific individual's past and future crimes to one another. The analyses suggested that individuals who are "rich" in terms of past criminal activities are likely to get even “richer” in the future. The analysis suggested not only that past crimes genuinely influence the probability of individuals committing crimes in the current; they also suggested that the effects were large compared to the effects of more traditional socio-demographic risk factors.

In Chapter 4 the focus changed from Sweden to Mexico, from individual to corporate behaviour, and from tax evasion to tax avoidance. The main explanatory mechanisms remained the same, however, and the chapter examined the role of both types of positive-feedback mechanisms. The analyses suggested that exposure to legal tax avoidance of others increased the propensity that a firm would engage in tax avoidance, and also that having engaged in tax avoidance in the past increased the likelihood of a firm engaging in tax avoidance in the current.

Chapter 5 used the same Mexican firm data but focused on tax evasion. Once again, considerable empirical support was received for the positive feedback mechanisms. The analyses suggested that firms that had engaged in legal tax avoidance in the past were more likely to evade taxes in the present, and the analyses also suggested that exposure to the tax evasion of others increased the risk of a firm starting to evade taxes.

The support for positive-feedback mechanisms is interesting in and of it self, but it also is important because it has implications for how we understand aggregate crime dynamics. When the first type of positive-feedback mechanism operates, individuals’ behaviour in part is explained by the behaviour of others. This simple but important idea was at the heart of Granovetter’s (1978) threshold model. Granovetter’s main idea was that whether or not individuals do X in part depends upon how many others already have done X and individuals' may differ from one another in terms of their "thresholds", i.e., how many others must have done X before they are willing to do the same.

A simple example can be used to illustrate the potential importance of this positive feedback mechanism for aggregate evasion dynamics. Assume two groups, each consisting of 100 individuals. In the first group, one individual has a threshold of 0, one has a threshold of 1, one has a threshold of 2, and so on up to the hundredth individual who has a threshold of 99. The person with a threshold of 0 will evade taxes at the very start irrespectively of what the others are doing. This person's evasion behaviour will make the person with the threshold of 1 also to evade taxes. Together they will trigger the person with the threshold of 3, and so on until all 100 individuals evade their taxes. The second group is identical with the first group with one small exception; instead of having one person with a threshold of 1 there are two persons with a threshold of 2. Also in this group the person with a threshold of 0 will evade taxes at the very start, but then the process stops because there is no one with a threshold of 1, i.e., there is no one who is willing to evade if only one other person has evaded. Granovetter's example is of course stylized and unrealistic but it highlights the contingent nature of these kinds of processes and how small and seemingly unimportant differences can set in motion (or prevent) processes that have considerable long-term effects.[60]

[60] The type of positive feedback process analysed in this thesis is considerably more complex than that considered by Granovetter, in part because it involves inter-actor as well as intra-actor feedback. These additional complexities, however, will further amplify the effects highlighted by Granovetter's model.

For reasons such as these, even groups of individuals who are virtually identical to one another in all relevant respects can exhibit considerable behavioural variations. This insight has been used by Glaeser et al. (1996) to explain the variation in crime rates between American cities. Somewhat puzzling, variations in crimes rates across time and space are much greater than one would expect from the corresponding variations in known crime-inducing factors. But if social interactions and the endogenous processes they give rise to are taken into account, these differences between cities become much less puzzling.

One aggregate pattern that often is seen as indicative of these kinds of positive-feedback processes is if the outcome distribution follows a highly skewed, so-called power-law distribution (cf., Barabasi and Albert 1999). As Cook, Ormerod, and Cooper (2004:1) expressed it: “Power law distributions of macroscopic observables are ubiquitous in both the natural and social sciences. They are indicative of correlated, cooperative phenomena between groups of interacting agents at the microscopic level.” That is, if the macroscopic patterns follow such a distribution it often is the result of a feedback process operating at the microscopic level. The “forest-fire” model of Biggs (2005), for example, which he used for explaining strikes and strike waves, generates these kinds of power-law distributed outcomes.

The agent-based analyses in Chapter 1 also showed that interaction-induced positive-feedback can generate highly skewed outcome distributions. But these analyses also suggested that the types of networks in which agents are embedded are likely to matter considerably for the link between micro and macro. The analyses showed that identical agents acting according to the same “logics” can generate vastly different macro outcomes depending upon the structure of the networks in which they are embedded. The analyses suggested that highly skewed outcome distributions only are likely to be observed if the agents are embedded in networks with highly skewed degree distributions.

Figure 6.1 shows how the various crimes considered in chapters 2 and 3 are distributed. The figure is based on crimes committed in the Stockholm County during the five-year period 1999-2003 and shows, for each type of crime, how many individuals committed one, two, three etc. crimes during these years. In order to make the details of the graphs readable, they only include individuals who committed at least one crime. When examining the graphs one should therefore imagine the existence of one extremely long bar extending far outside the right-hand side of the page which shows the number of individuals who committed no crimes at all.

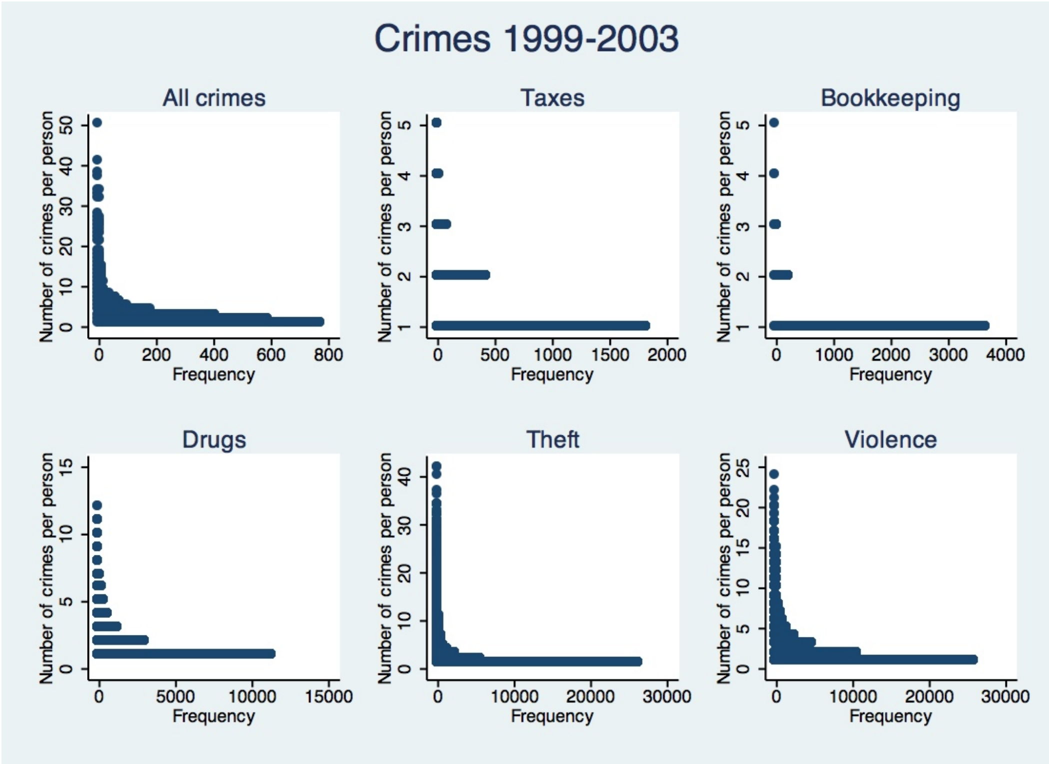

Figure 6.1. Distribution of criminal offenses among criminal offenders.

As can be seen from the graphs, all crime distributions are extremely skewed. The vast majority of the individuals committed no crimes at all. Among those who committed crimes, most committed one crime only, but irrespective of the type of crime, there is long tail of repeat offenders. The average number of crimes committed as well as the length of the tails varies from one type of crime to another, but the basic skewed shape of the distribution remains more or less the same.

As already discussed, the agent-based analyses in Chapter 1 suggested that outcome distributions like these are more likely to emerge if the networks within which the individuals are embedded have a highly skewed degree distribution, i.e., that the number of links sent to and received from others vary considerably from individual to individual. The only real network data available for this study was the kinship network analysed in Chapter 2. In that chapter we could see that crimes of kin had a considerable impact of its own on individuals' crime propensity, i.e., that the first type of positive feedback mechanism operated. The kinship network thus seemed to have causal efficacy but we never examined the degree distribution of the network.

As described in Chapter 2, the following kin types can be identified in the data: spouse, children, grandchildren, parents, grandparents, siblings, aunts, uncles, parents in law, brothers in law, and sisters in law.[61] Two individuals thus are linked to one another in this kinship network if one or more of these kinship relations obtain between them. The degree distribution of this kinship network is shown in Figure 6.2.

[61] Since the dataset only includes individuals who resided in Stockholm County at least once during the years 1990 to 2003, I only have data on kin who resided in Stockholm during those years. As mentioned in Chapter 2, I also have information on the identities of parents whether or not they resided in Stockholm, however, and hence we can identify siblings etc. even if the parents never resided in Stockholm.

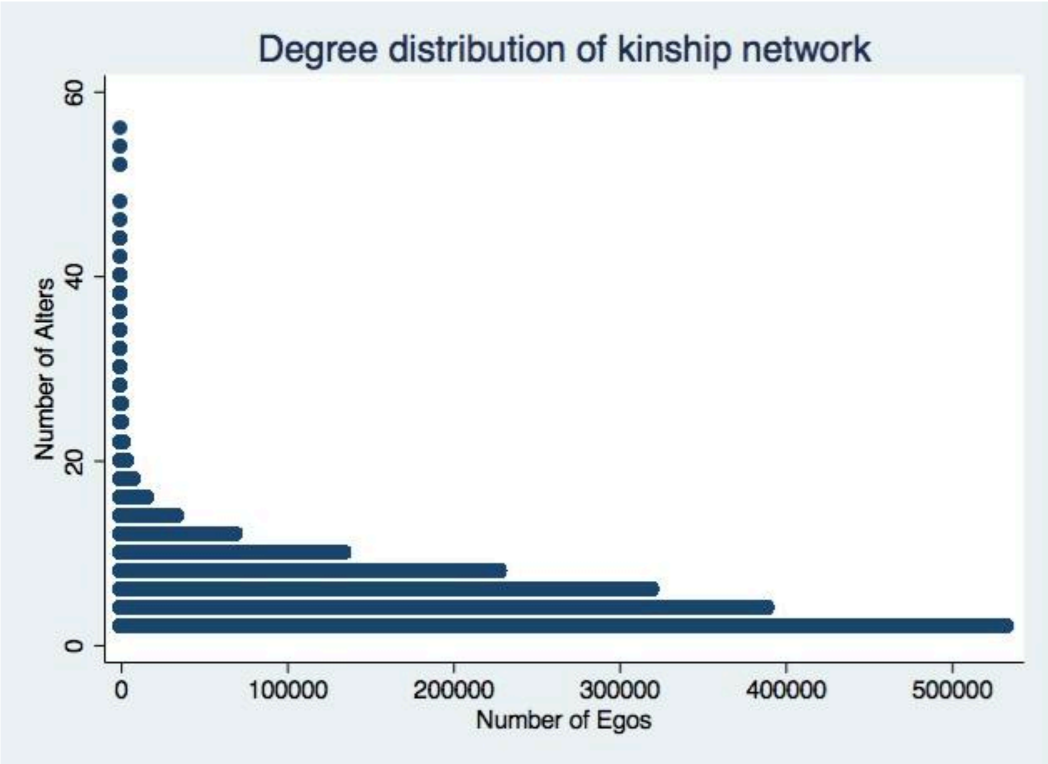

Figure 6.2. Degree distribution of kinship network in year 2000.

Figure 6.2 shows the degree distribution for the year 2000 (the distribution looks more or less the same for the other years). The graph should be read as follows: approximately 525,000 individuals were linked to one or two other individuals; about 390,000 individuals were linked to 3 or 4 other individuals; 320,000 individuals were linked to 5 or 6 other individuals, and so on. Of particular interest here is skew and the long tail of the distribution; although the mode degree was 1 and the median degree was 4, one individual out of twenty had a degree of 12 or greater. The kinship network thus has the type of skewed degree distribution that the agent-based analyses suggested is needed in order for skewed crime distributions to emerge.

The horizontal x-axis of Figure 6.3 shows the size of an individual's kin group (i.e., the degree of the individual's ego-centered kinship network), and the vertical y-axis shows the number of individuals who had a kinship group/degree this large or larger. Although the degree distribution is extremely skewed, it does not appear to be a power-law distribution. When plotting the data, the relationship between the degree (size of kin group) and the cumulative distribution appears approximately linear in a semi-log graph but not in a log-log graph. This suggests that the distribution is exponential rather than power-law distributed. The upper tail of the distribution more closely resembles a power-law distribution, however. If a linear OLS equation is fitted to the data, it suggests that the power-law exponent was equal to −2.61 in the 9+ degree interval, and the R^2-value of that model was .98 which suggests a reasonably good fit to the data.

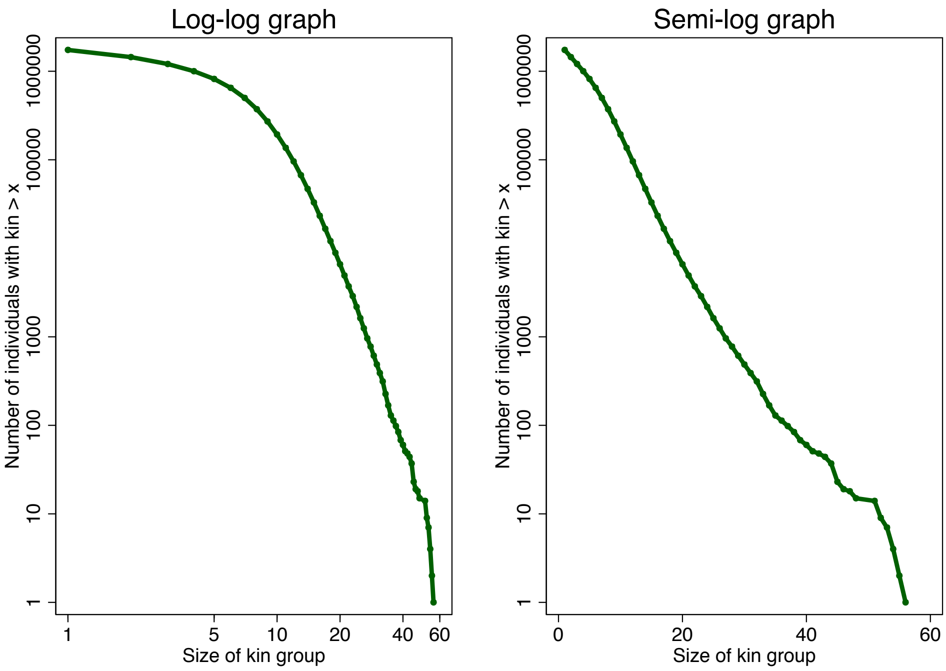

Figure 6.3. Log-log and semi-log graphs of the degree distribution of the kinship network in year 2000.

These macro-level patterns, coupled with the consistent findings in previous chapters about the importance of positive feedback for explaining individuals' evasion decisions, offer considerable arguments for redirecting research on tax evasion in a more sociological direction. As discussed in earlier chapters, tax research is a domain mainly occupied by economists. Although behaviourally oriented economists have considered many mechanisms of a sociological or social-psychological character, the field remains dominated by rather static decision-theoretic models where atomistic and under-socialized actors are seen as reacting to exogenously given changes in detection risks and penalty levels.

As argued by Biggs (2003; 2005), when positive-feedback mechanisms operate, aggregate dynamics, in part, are governed by an endogenous component where behaviour feeds onto itself. Although the process may be triggered by exogenous events, the magnitude of the ultimate effect depends to a considerable degree upon the endogenous dynamics, and the explanatory task then is not only to locate exogenous causes but also to unravel endogenous processes. This is an important insight that is as true for tax behaviour as it is for strike behaviour, the focus of Biggs' analyses. To understand macroscopic evasion patterns and dynamics, exogenous events like changes in tax codes or enforcement policies obviously are important, but much more scholarly attention must be given to endogenous processes through which taxation crimes breed more taxation crimes and the role of networks in conditioning such processes.

I believe that the research presented in this thesis has taken a small but important step in that direction. It has demonstrated the importance of positive feedback processes and it has indicated the high potential of further research along these lines.

The importance of endogenous feedback processes also has important policy implications. The analyses of the Stockholm data suggest that network ties to past offenders are of considerable importance in and of themselves for the likelihood that an individual will commit a taxation crime, and the same is true for "ties" to an offending self in the past, i.e., if an individual has committed crimes in the past he/she is much more likely to commit tax crimes in the present. For example, of the 1,367 individuals who committed tax-evasion or bookkeeping crimes in Stockholm County in

2003, almost 20 per cent had someone in their kinship network who had committed a crime in the past as compared to less than 7 per cent among those who had not committed any tax crime in 2003, and almost 60 per cent had themselves committed a crime in the past as compared to less than 12 per cent among those who had not committed any tax crime in 2003.[62] From a crime-prevention perspective, the analyses reported in this thesis hence underscore the importance of focusing on the relational aspects of crime and that interventions that introduce wedges into the social-influence processes that propagate criminal behaviour from one individual to another (or interpersonally from one point in time to another) are likely to be of considerable importance. As noted earlier, it is not until the last few years that social-network inspired ideas have come to be adopted by law-enforcement agencies, and then typically only for dealing with organized crime (see Leinfelt and Rostami 2012). The analyses reported here suggest that a network perspective also can be highly useful for dealing more effectively with "un-organized" crime.

The results from the analyses of the Mexican data similarly emphasized the importance of positive feedback processes and social interactions, and therefore lead to the same general policy implications as the analyses of the Swedish data did. For example, the analyses suggested that firms that had avoided taxes in the past were more likely to do the same also in the present, and firms that were embedded in high-avoidance environments were more likely to avoid taxes than firms that were embedded in other kinds of environments.

[62] To avoid any misunderstanding, the reason for the total number of tax-evasion and bookkeeping offenders being 1,367 rather than the 1,671 (1007+654) one may have expected based on the results reported in Chapter 3, is that 294 individuals committed both types of offenses in 2003.

Given the consistent positive-feedback patterns revealed in this thesis, the so-called broken-window thesis with its policy implications (e.g., Kelling and Coles 1996; Gladwell 2000) appears applicable and relevant. The broken-window thesis derives its name from the observation that if a broken window in a building is left unrepaired, it will soon result in all windows being broken. For this reason, policy-makers must not disregard the seemingly small and inconsequential because minor events and behaviours often cascade to become more serious outcomes. A successful strategy for reducing tax evasion therefore should focus on reducing problems when they are small, in particular to reduce the room for tax avoidance since this appears to be an early and important stepping stone into tax evasion.

Comparing the Swedish and Mexican cases one cannot but conclude that the Mexican state could gain much by studying in more detail the Swedish tax system. The Swedish tax system is far more transparent and easy to navigate than the Mexican system is, and does not have nearly as many special exceptions and deductions as does the Mexican system. There appear to be much more opportunities for tax avoidance in the Mexico than in Sweden, and since the empirical results indicate that tax avoidance often lead to tax evasion, a simplification of the Mexican tax system seems called for that reduces the opportunities for legal tax avoidance and thereby closes important paths into tax evasion.

Furthermore, as noted in earlier chapters, one typical form of corporate tax evasion in Mexico is the "sale" of invoices. The companies issuing the bills that the focal companies buy in order to make deductions that reduce taxes typically are companies with large losses that in practice already have stopped operating. They can "sell" invoices up to the amount of losses and still not pay any additional taxes. As discussed above, this type of tax evasion is mainly spread by social interactions among taxpayers and it seems likely that it can only be stopped if tax authorities assign specific auditors to those companies so that the filling of taxes is closely supervised.

From an equity perspective there also are policy lessons to be learned by comparing the Swedish and the Mexican systems. Income inequality and poverty levels are higher in Mexico than in any other OECD country (see OECD 2008). Inequality in the total after tax and transfer household income, adjusted for household size, is one and a half times higher in Mexico than in a typical OECD country and twice as high as in low inequality countries, such as Sweden (as measured by the Gini coefficient). Although these disparities only partly reflect differences in the tax systems, differences in tax systems and the enforcement of tax laws clearly play an important role. For example, the fact that dividends and most capital gains are exempted from tax in Mexico surely must contribute importantly to the high inequality levels in Mexico since it mainly are the already well to do who have such incomes.[63] Some of the analyses in Chapter 4 also suggested that Mexico deviates noticeably from countries such as Sweden in terms of tax collection rates. Although nominal tax rates are rather high in Mexico, the de facto taxes collected tend to be low by OECD standards.

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[63] Although from January 2014 the fiscal reform to the Income Tax imposed a 10 per cent tax on dividends paid to private persons and residents abroad.

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