Tax Evasion and Social Interactions: An Experimental Approach

Bernard Fortin*       Guy Lacroix†      Jean-Louis Rullière ‡
Marie-Claire Villeval§

December 2003
Very preliminary. Not to be quoted.

Abstract

This paper first develops a theoretical framework for analyzing the impact of social interactions on tax evasion behavior. Using Manski’s (1993) nomenclature, our approach takes into account social conformity effects (expressing endogenous interactions) and fairness effects (expressing exogenous interactions). The latter reflect the taxpayer’s perception of how he is treated by the tax system relative to others. Our model also allows for individual unobservable attributes common across reference group members (expressing correlated effects). To test our model, we perform a tax evasion experiment involving 12 sessions of 15 participants. In each round of a session, participants are told the tax rate and the audit probability they face and those faced by the other participants (their reference group). In the second part of each session, the participants are given an additional information about the number of evaders and the mean reported income by the other participants in the previous period. Only information at convergence to an equilibrium is used in the econometric analysis. To estimate the model, we develop a two-limit simultaneous tobit with fixed group effects. Nonlinearities introduced by this approach allow to identify the model without any exclusion restrictions on exogenous interactions variables. Results indicate the presence of fairness effects but reject the presence of social conformity and correlated effects.

*Département d’économique, Cirpée and Cirano, Université Laval, Québec, Canada. E-mail: Bernard.Fortin@ecn.ulaval.ca
†Département d’économique, Cirpée and Cirano, Université Laval, Québec, Canada. E-mail: Guy.Lacroix@ecn.ulaval.ca
‡GATE (CNRS - Université Lumière Lyon 2 - Ecole Normale Supérieure LSH), France. E-mail: Rulliere@gate.cnrs.fr
§GATE (CNRS - Université Lumière Lyon 2 - Ecole Normale Supérieure LSH) France, and IZA, Bonn, Germany. E-mail: Villeval@gate.cnrs.fr
1 Introduction

Under the standard view of tax evasion first developed by Allingham and Sandmo (1972) and Yitzhaki (1974), the taxpayer is an isolated expected utility maximizer who makes a portfolio decision under uncertainty. In this approach, cheating on taxes is a simple game with the tax authority whose payoff is either a lower tax burden or, with a given probability, a larger penalty.

This theoretical framework assumes that the taxpayer is completely individualistic and amoral, and is therefore not affected by social norms in his decision. It thus ignores the influence of social interactions upon his willingness to underreport income. However, if social interactions play a significant role in individual tax evasion behavior, and no account is made for this in the analysis, predictions of the effects of tax or fraud prevention policies can be seriously misleading. As is well known since Schelling (1978) and Akerlof (1980), interdependent behavior may generate multiple equilibria and exhibit contagion and epidemic features through a “social multiplier effect”.

There are many factors that can explain the presence of social interactions in tax evasion behavior (e.g., Andreoni et al. 1998). First, Erard and Feinstein (1994) insist on the role of guilt and shame in tax compliance behavior. In a related way, Gordon (1989) and Myles and Naylor (1996) argue that an individual can derive a psychic payoff from adhering to the standard pattern of reporting behavior in his reference group (social conformity effect). Second, through learning from his peers, a taxpayer may find less costly ways to underreport income, to lower the risk of being caught or to reduce penalties associated with tax audits (social learning effect). Third, the individual’s perception of the fairness of his tax burden may influence his tax evasion decisions. Indeed, Spicer and Becker (1980) have provided evidence that people who believe that the tax system treats them unfairly relative to others tend to engage in more tax evasion to restore equity (fairness effect). Finally, the degree of taxpayers’ satisfaction with government (e.g., Cowell 1990, Pommerehne et al. 1994), or their ability to influence the process of political choices notably by voting (Feld and Tyran, 2002), may also be considered as moral and social factors affecting one’s decision. Thus if a taxpayer believes that the government is corrupted and incompetent, this may affect his compliance behavior (satisfaction effect).

While most economists would probably agree with this taxonomy, they would not be unanimous as regards the magnitude and even the existence of these social interaction effects. For instance, the experiment run by Spicer and Hero (1985) shows that when the others’ decisions do not influence one’s earnings, providing information about their evasion behavior does not always influence individual compliance. At a more general level, the importance of social interactions has recently become a controversial area of research in economics. The main reason is that it has been recognized, since in particular Manski’s (1993) path-breaking analysis, that
measuring social interactions effects raises difficult identification and estimating problems. Moreover when appropriate data and econometric methods are used to estimate these effects, the latter are often small or even non-existent as determinants of individual outcomes (e.g., Evans, et al. 1992, Aaronson 1998, Krauth 2002).

The identification problem arises from the fact that interdependent behavior takes different forms that may be difficult to isolate. Thus, using Manski’s (1993) nomenclature, the propensity of an agent to evade may vary with the behavior of the group (endogenous interactions), but it may also vary with exogenous characteristics of the group members (exogenous or contextual interactions). For instance, in a model of tax evasion behavior within a population, social conformity and social learning effects reflect endogenous interactions while fairness and satisfaction effects reflect exogenous interactions, given the parameters of tax and fraud prevention policies. Moreover, the presence of a correlation between tax evasion activities of individuals in a group may not solely reflect interdependent behavior. Indeed, agents in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments (correlated effects).

In a simple linear-in-means regression like model where all these three effects are present, Manski (1993) has shown that equilibrium outcome cannot distinguish endogenous effects from exogenous effects or correlated effects. In this context, it is impossible to identify the true nature of social interactions. This so-called ”reflexion problem” arises because the average behavior of the group is itself the mirror of the behavior of individual members of the group. A number of researchers (e.g., Brock and Durlauf 2001a and 2003, Moffitt 2001) have analyzed alternative models that allow for identification (e.g., nonlinearity of the endogenous group effect on individual behavior, exclusion restrictions on exogenous interaction variables, randomization of group composition). However, the validity of these models rests on the credibility of the identifying assumptions imposed to the model which in part depends on the nature of the data used to estimate the model.

Even when an interactions-based model is identified, its estimation raises serious econometric problems. In particular, the mean group decision, which appears as a regressor, is likely to be endogenous. Two reasons explain this endogeneity. First, since individuals tend to select their peer groups, their observed and unobserved characteristics may very well be highly correlated (sorting bias). Also individuals in a group are likely to face common shocks. Second, since not only the individual’s behavior is affected by his mean group behavior but conversely the mean group behavior is affected by the individual’s behavior, this is a source of a simultaneity problem specially in small groups (simultaneity problem).

Several studies that correct for the sorting bias show that the endogenous interaction effects shrinks or even completely disappear. For example, by using micro-simulation-based estimations, Krauth (2002) finds that the actual peer effect on teen smoking is decreased by half when compared to standard estimation procedures. This result suggests that papers re-
porting important peer effects should be taken cautiously if they ignore those selection effects. Also, Krauth shows that the simultaneity bias may be important in small peer groups. Therefore, the use of appropriate data and econometric models is required to provide a robust test of the existence of social interactions effects.

Few studies have analyzed the impact of social interactions on tax evasion activities. One basic reason is that almost by definition the latter are very hard to measure. The most reliable information about noncompliance is based on actual tax returns that have been audited.\footnote{For an early econometric study using data from audits conducted on a stratified random sample of individual income tax returns, see Clotfelter (1983). He used information from the Taxpayer Compliance Measurement Program (TCMP) of the U.S. Internal Revenue Service.} However, these data are not readily available. When they are, they do not usually provide information on social interaction variables nor do they reveal the nature of the reference group (or the “neighborhood”) with whom an agent may interact. This information is required to estimate social conformity effects (Manski 2000). An alternative source of information comes from randomized surveys (e.g., Sheffrin and Triest 1992). One advantage of these data is that they can provide subjective information about variables such as the taxpayer’s reference group or his degree of satisfaction with respect to government expenditures. But a substantial fraction of tax evasion activities are likely to be underreported in these surveys (Elffers \textit{et al.} 1987).

Few attempts have also been made to document the impact of social interactions on tax compliance in experimental economics and evidence is contrasted. Recent attempts have been done to identify social interactions in the laboratory, in the field of criminal activities such as stealing (Falk and Fischbacher 2002) or public good games (Falk \textit{et al.} 2002), but not in the field of tax compliance. An exception is when the subjects receive a public good which size depends on the tax contributions of all group members. In this framework, the extent of individual compliance is influenced by the others’ reporting decisions and moral constraints are a disincentive to evade (Bosco and Mittone 1997).

In this paper, we present results from an experiment on the impact of social interactions on tax evasion behavior. We first attempt to show how in general the use of laboratory experiments can generally be very useful for that purpose (Section 2). In Section 3, we develop a theoretical model of tax evasion with both endogenous and exogenous social interactions. More specifically, it extends the standard Allingham-Sandmo-Yitzhaki model to allow for social conformity and fairness effects. Section 4 describes the tax evasion experiment we have designed in order to estimate and to test our theoretical model. In the first part of this experiment, each member of a group receives an endowment and is requested to give back a percentage of this endowment. The reported income can be audited and participants have to pay a penalty if they are caught cheating on the reported income. In the second part of the experiment, each member of the group is informed on the number of group members who
underreported in the previous period and the average reported income before deciding on their own report in the current period. Section 5 discusses our econometric approach. We develop a two-limit simultaneous tobit approach with fixed group effects to estimate our model. Our analysis suggests that the nonlinearity introduced by the tobit approach ease the identification of the model even without any exclusion restrictions on exogenous interactions variables. In a sense, our approach extends the Brock-Durlauf (2001a) discrete choice model to the case where the censored choice variable (tax compliance decision) is a mix of discrete and continuous variables. Our simultaneous tobit takes into account both selection and simultaneity biases. Section 6 contains some descriptive statistics of our experiment and discusses the econometric results. Our findings are consistent with the presence of fairness effects but reject the presence of social conformity and correlated effects. Moreover, according to our results, the individual tax rate, the probability of audit, gender and a measure of inequity aversion all have a significant influence on tax compliance behavior. Section 7 concludes.

2 Why use experiments to study social interactions?

The determinants of tax evasion can be measured empirically through different types of data but not all provide the same opportunities to isolate the effects of social interactions on individual decision. Experimental data have the potential of providing more information on such issues as standard data sources such as audits and survey data.\(^2\)

While audit data provide the most reliable information on tax evasion, they are of very little use for the analysis of social interactions. In particular, they usually contain no information about the reference group with whom each taxpayer may interact (neighbors, parish, colleagues, etc.).\(^3\)

Survey data do provide valuable information on individual characteristics and sometimes subjective information on the nature of each taxpayer’s reference group. However, they usually do not contain any reliable information about the tax evasion behavior and the characteristics of these groups. This point is important since some knowledge of these variables is required to estimate the impact of social interactions on individual behavior. Moreover, even when the reference group is known, one needs to take into account its endogeneity in the model to be estimated. As discussed above, the basic reason is that individuals tend to self-select in groups or communities that share their own attributes, creating a correlation between the unobservable group-specific error term and the exogenous characteristics of the individuals in the group. This implies that suitable instruments not correlated with this error term but correlated with

\(^2\)A fourth source of information not discussed here comes from tax amnesty data (Andreoni et al. 1998).

\(^3\)Manski (1993, 2000) was one of the first to emphasize that the need to know group composition \textit{a priori} is a fundamental problem in interactions-based models.
the decision to be a member of the group are required, something that is difficult to come by with survey data.

In contrast, data from laboratory experiments allow the researcher to control the reference group with whom the agent interacts. For instance, the researcher can determine the number of subjects exogenously and randomize the group composition. Thus in the experiment discussed in this paper, each subject’s reference group consists of all other participants in a session (14 individuals) and the subjects have information about the decisions of the other participants of their own session only. Also, experimental data usually provide information on social background characteristics of the participants.

Moreover, interdependent behavior takes different forms that may be difficult to identify by means of field data. As mentioned in the introduction, an agent’s tax evasion behavior may involve both endogenous and exogenous social interactions as well as correlated effects. This raises identification problems that are hard to resolve - namely, how to distinguish within group correlations that arise from endogenous and exogenous social interactions from those that arise for other reasons. For that matter, the precise design of a tax evasion experiment may help to solve the identification problem in many ways. For instance, Moffitt (2001) has emphasized that, in the absence of correlated effects, it is in general possible to identify the social interactions effects. Therefore, a random assignment to a session limits the probability of similar unobserved individual characteristics and constitutes a possible identification mechanism. Of course, this is not enough to rule out correlated effects since the participants from a same school who have registered to the experimental sessions voluntarily may present the same unobserved individual characteristics that the experimentalist cannot control for.

The presence of a nonlinearity in the impact of the reference group’s behavior on individual behavior may also help to identify interactions-based models with self-consistent beliefs (Brock and Durlauf 2001b). Basically, the idea is that in a linear-in-means model where all the mean group characteristics analogous to the individual characteristics appear as explaining variables, the mean group choice is proportional to the mean group characteristics. As a result, the model is unidentified since it is not possible to isolate the effect of the mean group choice from that of the mean group characteristics. Of course, this is not in general the case when there is a nonlinear relationship between the mean group choice and the individual choice. Note however that identification hinges critically on knowing the specific form of the nonlinearity, which depends on the distributional assumptions imposed to the random terms. In our tax evasion experiment, the endogenous variable, which is the amount of income reported by the subject, is bounded between 0 and 100. Therefore, given that 43.5% of our data are censored either at 0 or at 100, the model involves a nonlinear relationship between the mean response of the reference group and the individual’s behavior. This nonlinearity helps to identify the model.
Beyond the identification problem, experiments also permit to circumvent some difficulties associated with audit or survey data, such as the endogeneity of the audit probability. In our experiment, the audit strategy is random and the intensity of evasion has no influence on the audit policy (exogenous probability). Note also that the use of a computerized device avoids measurement errors likely to distort field data, since evasion in the laboratory can be perfectly scored and responses are necessarily honest. Furthermore, the opportunity to play several periods per round under the same tax and audit regime up to convergence to a social equilibrium makes rational expectations or even perfect foresight of the reference group’s behavior a reasonable assumption. Also, experiments enable to hold the tax reporting institution constant and to test in a limited period of time and for a limited cost the impact of various tax regimes and audit policies.

At a general level, by controlling extensively for the environment and the preferences, ensuring a control of the agents’ sets of choices and information conditions, laboratory experiments offer interesting opportunities to measure the effects of social interactions on individual outcomes. This gives tax evasion data from laboratory experiments an important advantage with respect to other sources of data.

Of course, one important limitation of laboratory experiments is that it may be difficult to replicate the moral, emotional and social dimensions of the tax compliance decision (Andreoni et al. 1998). On the one hand, laboratory experiments have enabled to identify the importance of morale in economic interactions such as employer-employee relationships or the importance of emotions such as reciprocity or inequity aversion notably in bargaining games. On the other hand, the use of a neutral wording in the protocol, necessary to avoid any contextual bias, may not allow the participants to endorse the same moral rules as regards tax evasion than in a real setting. Therefore, it could be hazardous to extrapolate results from experiments to the real life without introducing a number of caveats.

3 A Model of Tax Evasion with Social Interactions

3.1 Modelling the individual tax evasion decision

In this section, we present a model that introduces endogenous and exogenous social interactions among taxpayers into the standard Allingham-Sandmo-Yitzhaki tax evasion model. In particular, it takes both social conformity and fairness effects into account.\(^4\)

\(^4\)For obvious reasons we ignore a third kind of social factor which is the degree of taxpayers’s satisfaction with government (e.g., Smith 1992; Alm et al. 1992).
Consider an individual $i$ who is a member of a reference group of $N$ agents, $N$ being exogenous. His horizon decision is one period. His income $I$, normalized at 1, is unknown to the tax authority and is exogenous. All individuals in the group have the same income. The individual faces a flat tax rate $t_i$ on his reported income. He must decide how much income to report $D_i$ (which reflects his tax compliance behavior), with $0 \leq D_i \leq 1$, knowing that with probability $p_i$, his tax return will be audited. If the individual is caught cheating, he must pay the amount of evaded tax, $t_i F_i$, with $F_i = 1 - D_i$, plus a penalty at a rate $\theta \geq 0$ on this amount, $\theta t_i F_i$. For simplicity, the penalty rate is assumed the same for all agents. If the individual is not audited, his net income will be $1 - t_i D_i$. On the other hand, if he is audited his net income will be $1 - t_i D_i - (1 + \theta) t_i F_i = 1 - t_i D_i - (1 + \theta) t_i (I - D_i)$. Expected utility, $EU_i$, is assumed to consist of two separable components:

$$EU_i = \{(1 - p_i)u(1 - t_i D_i) + p_i u(1 - t_i D_i - (1 + \theta) t_i (1 - D_i))\} + S(D_i, X_i). \quad (1)$$

The first component within embraces is the private expected utility associated with tax compliance behavior, that is, with a choice of $D_i$. Assuming that the individual is risk averse, private utility $u(\cdot)$ is increasing and concave in consumption. The second component, $S(D_i, X_i)$, is the social (ex-ante) utility associated with tax compliance. This component is assumed to depend on the fraction of income reported, $D_i$, and on a vector $X_i$ of exogenous (to the individual) variables to be defined below.\footnote{The separability assumption between private and social utilities has also been made by Brock and Durlauf (2001a).} Moreover, the marginal social utility of tax compliance, $s_i \equiv \partial S/\partial D_i$, which is negative when it is a disutility, is assumed to depend only on $X_i$:

$$s_i = s(X_i).$$

Therefore, $S(D_i, X_i)$ is an affine function of $D_i$:

$$S(D_i, X_i) = s(X_i) D_i. \quad (2)$$

The vector $X_i$ includes a number of variables. First, we assume that the marginal social utility of tax compliance depends on $\overline{D}^-_{-i}$, the individual $i$’s subjective expectation of the average tax compliance of the other agents of his reference group. A positive effect corresponds to a social conformity effect. In that case, preferences exhibit so-called strategic complementarities (Brock and Durlauf 2001a). A negative effect corresponds to a social anti-conformity effect. In that case, the individual enjoys to deviate from the tax compliance behavior of the other members of his reference group. Moreover, the marginal social utility is assumed to be decreasing with the difference between the individual’s tax rate and the average tax rate faced by the other agents, $t_i - \overline{t}_{-i}$, and with the difference between the individual’s audit probability and the average audit probability faced by the other agents, $p_i - \overline{p}_{-i}$ (fairness effect). Finally, $X_i$ includes a sub-vector $Z_i$ of observable individual attributes (e.g., gender), a sub-vector $\overline{Z}_{-i}$ of the corresponding average observable attributes of the agents other than $i$ and a random term $\epsilon_i$ that captures non-observable (to the analyst) individual-specific attributes and...
attributes that are common to all individuals in the group. The individual knows $\epsilon_i$ when making his decision. This variable allows to introduce a direct link between the theoretical model and its econometric implementation. Therefore, one gets:

$$s(X_i) = s(D^e_{-i}, t_i - \bar{t}_{-i}, p_i - \bar{p}_{-i}, Z_i, Z_{-i}, \epsilon_i), \text{ with } s_1 \geq 0, s_2 \leq 0, s_3 \leq 0. \tag{3}$$

We assume that the level of public goods does not influence the individual’s utility, or alternatively, that public goods are separable from private consumption in the utility function and therefore do not influence individual behavior. Substituting equations (3) and (2) into (1) and assuming that preferences satisfy Von Neuman-Morgenstein axioms, the individual’s problem is to choose his preferred amount of income to report to the tax authority, $D_i$, so as to maximize his expected utility (1) subject to the inequality conditions $0 \leq D_i \leq 1$.

The Kuhn-Tucker first-order conditions associated with this problem can be used to solve for the individual’s optimal level of reported income. Equivalently, and to present a formulation more in line with the econometric specification, let us first solve the optimization problem while ignoring the inequality conditions on $D_i$. The equation for $D^*_i$, the latent variable associated with $D_i$, can be written as:

$$D^*_i = D^*(t_i, p_i, D^e_{-i}, t_i - \bar{t}_{-i}, p_i - \bar{p}_{-i}, Z_i, Z_{-i}, \epsilon_i). \tag{4}$$

Note that the individual’s income and the penalty rate $\theta$ are supposed constant. Therefore they can be ignored in (4). Now, given the inequalities conditions on $D_i$, the relationship between the (observed) variable $D_i$ and the latent (unobserved) variable $D^*_i$ is given by:

$$D_i = \mathbb{I}(0 < D^*_i < 1)D^*_i + \mathbb{I}(D^*_i \geq 1), \tag{5}$$

where $\mathbb{I}(A)$ is an indicator function for the event $A$ which takes the value zero or one.

On the basis of this model, it is possible to derive the six following predictions with regard to individual tax evasion behavior. (1) A risk-averse individual will always underreport his income (i.e., $D_i < 1$) whenever $1 - s(X_i)/tu'(1 - t) - p_i(1 + \theta) > 0$, that is, whenever the expected return of evaded taxes is strictly positive, with due allowance for the marginal social cost of tax evasion expressed in terms of consumption, $s(X_i)/tu'(1 - t)$. Interestingly, the observed high levels of tax compliance relatively to that predicted by simple expected utility models of behavior (see Andreoni et al. 1998) may be partly explained by large marginal

---

6One could allow the vectors $Z$ and $Z_{-i}$ and the scalar $\epsilon_i$ to influence the private utility component of the individual’s expected utility. However, this would not change the comparative static of the model in any significant way.

7See Bernasconi and Zanardi (2001) for a critic of these axioms as applied to tax evasion behavior. They develop an alternative approach, based on Tversky-Kahneman (1992) loss aversion, which assumes that the taxpayer is influenced by gains or losses with respect to some reference level of income.

---
social costs. The former inequality indicates that the decision to evade is affected by all parameters of the model.

The five next comparative static predictions concern the impact of exogenous variables on the amount reported by individual $i$ assuming an interior solution: (2) $\partial D_i/\partial t_i =? $ (under decreasing absolute risk aversion); (3) $\partial D_i/\partial p_i \geq 0$; (4) $\partial D_i/\partial D_{-i} \geq 0$; (5) $\partial D_i/\partial (t_i - \overline{t}_{-i}) \leq 0$; and (6) $\partial D_i/\partial (p_i - \overline{p}_{-i}) \leq 0$. Proposition (2) says that the impact of an increase in the tax rate can be positive or negative on tax compliance. This impact can be decomposed into the sum of two effects with opposite signs. The first effect which is positive (see Yitzhaki 1974), has raised much discussion in the literature since it is rather counter-intuitive. It arises because the penalty is proportional to the amount of evaded tax. Therefore, an increase in the tax rate involves no substitution effect between the individual’s private consumption when he is audited and when he is not. However it reduces income, which in turn induces the individual to cheat less as long as his absolute risk aversion increases with a decrease in income. The second effect is due to the presence of a social component in the individual’s utility, which depends on tax compliance. Assume that the marginal social utility of tax compliance $s(X_i)$ is positive. The price (in terms of taxes paid) of tax compliance increases with an increase in the tax rate. Therefore, this effect will induce the individual to reduce his level of tax compliance. Interestingly, our model predicts that in the presence of a social component in the individual’s utility, it is possible that an increase in the tax rate stimulates tax evasion, which is a more intuitive result.

Proposition (3), first demonstrated by Allingham and Sandmo (1972), says that, as one would expect, an increase in the audit probability encourages tax compliance. Proposition (4) says that an increase in the average amount of income reported by the reference group encourages tax compliance (social conformity effect). Finally, propositions (5) and (6) indicate that an increase in the difference between an individual’s tax rate and that of his group (for a given level of the individual’s tax rate) and in the difference between the individual’s audit probability rate and that of the group (for a given level of the individual’s probability rate) reduces tax compliance (fairness effects). These last three propositions are due to the fact that an increase in the marginal social utility of tax compliance, $s_i$, induces the individual to report more income to the authority.

### 3.2 Social equilibrium with tax evasion

We assume that the individual acts non-cooperatively and does not take into account the effect of his decision on the choices of others via expectations formation. In order words, he makes his tax compliance decision conditional upon his expectations about the average amount of income reported by the other members of his group, $D_{-i}$. Therefore, to close the model, assumptions have to be made about the way individuals form their expectations. We must
in particular specify how the latter relate to the information available to the individual at the
time of his decision. This issue is crucial since the estimate of the social conformity effect is
likely to be strongly affected by the assumptions made about expectations. Instead of relying
on an ad hoc mechanism (e.g., myopic, adaptative), we have chosen the following approach
in our experiment. For any particular round, the game is repeated a number of periods until
a certain convergence criterion is met. At each period \( t > 2 \) of a round, this criterion is
expressed in terms of a small percentage difference (in absolute value) between the average
amount reported by the group in the two previous periods:
\[
\left| \frac{(D_{t-1}^t - D_{t-2}^t)}{D_{t-2}^t} \right| \leq 0.05.
\]
Further, for \( t > 2 \) each individual \( i \) is given information on \( D_{t-1}^t - D_{t-1}^i \) and equivalently on \( D_{t-1}^t \)
(since the individual is assumed to recall his own former decision). Therefore, if there exists a
social equilibrium and to the extent only information upon convergence is used for estimating
the model, one has: \( \overline{D}_{-i}^e \approx \overline{D}_{-i} \), since, by definition, this equality must be satisfied at the
(Nash) social equilibrium. This approach allows us to assume self-consistent beliefs in our
estimations.

The equilibrium condition of the model is thus obtained using \( \overline{D}_{-i}^e = \overline{D}_{-i} \) and replacing
\( \overline{D}_{-i} \) by \( \frac{1}{N-1}(\overline{D}N - D_i) \) into the latent equation (4). Then substituting this equation into (5)
and isolating \( D_i \) as a function of \( \overline{D} \) and the vector \( x_i \) of exogenous variables other than \( \overline{D}_{-i}^e \)
on the right-hand side of equation (4), one obtains: \( D_i = D(\overline{D}, x_i) \). Adding up over the \( N \)
individuals and dividing by \( N \), one gets the following equilibrium condition:
\[
\overline{D} = \frac{\sum_{i=1}^{N} D_i(\overline{D}, x_i)}{N} = G(\overline{D}, x),
\]
where \( x \) is the vector of all exogenous individual and policy variables of the model. Since
the function \( G(\overline{D}, x) \) is continuous and that the support of \( \overline{D} \) is compact, it is immediate
from Brouwer’s fixed point theorem that there must exist at least one solution for \( \overline{D} \) that
satisfies this condition. However, there can be multiple equilibria for equation (6). Brock and
Durlauf (2001b) have strongly insisted on this possibility in interactions-based models. In
the econometric section, we will discuss this possibility and will show that it is related to the
so-called coherency conditions of the model.

---

8 After ten iterations, the round is stopped if no convergence has been reached and the information is discarded.
9 If there is a new realization of the random term \( \varepsilon_i \) at each period (\( \varepsilon_i \) is therefore replaced by \( \varepsilon_i^t \)) and
that individuals do not communicate, the perfect foresight equilibrium is replaced by a rational expectations
equilibrium, which implies: \( \overline{D}_{-i}^e = E(D_{-i}) \).
3.3 Social multiplier

In the literature on social interactions, one often stresses that the predictions of the effect of changes in the economic environment on aggregate behavior can be seriously biased if one does not take social interdependencies into account (e.g., Akerlof 1980, Aronsson et al. 1999, Glaeser et al. 2003). In our set-up, this can be illustrated by the following very simple example. Let us assume that the data on reported income are generated by the following linear model with social conformity: 

\[ D_i = a + bt + \gamma D^{e} \]

with \(0 < \gamma < 1\). At the social equilibrium, \(D^{e} = D\) and therefore \(D = a + bt + \gamma D\). The effect of a change in the tax rate on average reported income is thus given by: 

\[ \frac{dD}{dt} = \frac{b}{1 - \gamma}, \]

while at the individual level its effect is given by \(\partial D_i / \partial t = b\) (conditional on the level of individual expectations). The ratio between these two effects, \((dD/dt) / (\partial D_i / \partial t)\), and which is often referred to as the ”social multiplier”, is given by \(1/(1 - \gamma)\). This expression reflects the effect of social conformity on aggregate behavior. If for instance \(\gamma = .5\), the social multiplier is 2. This indicates that the average impact of a change in the tax rate at the aggregate level is twice its effect at the individual level.

In our model, the social multiplier is obtained by differentiating equation (6) with respect to any component \(x_j\) of \(x\). One gets an expression that generalizes the one obtained in our simple example:

\[ \frac{dD}{dx_j} = \frac{1}{(1 - \partial D_i / \partial D)} \]  

The expression on the right-hand side of this equation is the (local) social multiplier of tax evasion in our model. So long as \(\partial D_i / \partial D\) is positive but smaller than one (social conformity effect), this social multiplier will be greater than unity.

4 Experimental design

The purpose of our experiment is to generate data that allows to estimate and test our model of tax evasion with endogenous and exogenous social interactions. It thus belongs to both categories of experiments defined by Roth (1995) and reminded by Torgler (2002): it aims both to speak to theorists and to search for facts. Our experiment consists of two parts (see instructions in Appendix A). In the first, the participants are not informed on the behavior of their group members. In the second part they are told about the average response of others in the previous period.

\[ ^{10}\text{We assume that the number of individuals in the group is large, so that } D^{e} \text{ can be approximated by } D. \]
Each subject is allocated to a group of 15 participants. The first part of the experiment consists of 5 rounds. It corresponds to the no-information condition ("NOINF" treatment) and it leaves no opportunity for social interactions. At the beginning of each round, each participant receives the same initial exogenous "endowment" of 100 points which constitutes his income. He is requested to give back a percentage of his income (a "deduction rate"). There are 5 different tax rates, with each rate randomly assigned to 3 participants. This is common knowledge. Each participant is told that these paybacks will go into scientific research funds (i.e., the lab gets this amount of money back). To satisfy this request, the participant must report an amount, bounded by 0 and 100, to which the tax rate will apply. He is informed that his reported income can be audited according to a certain probability and that this audit will entail the payment of a fine (a "penalty") if the reported income is lesser than his endowment. There are 5 audit probabilities, with each audit probability randomly assigned to 3 participants. This is also common knowledge. The participants are informed that the probabilities are independent of the reported amounts. It should be noted that the distribution of individual tax rates is independent of the distribution of the audit probabilities. Three possible situations determine the payoffs:

a) If the reported income is not audited, the tax rate applies to the reported income and the participant’s payoff is given by the difference between the endowment and the tax payment.

b) If the reported income is audited and if it equals the endowment, the tax rate applies to this reported income, i.e. the total income, and the payoff of the participant is given by the difference between the endowment and the tax payment.

c) If the reported income is audited and if it is lesser than the endowment, the tax rate applies not to the reported income but to the endowment on top of which a penalty must be paid. This penalty is obtained by applying the tax rate to the evaded income (penalty rate of 100% on unpaid taxes). In this case, the payoff corresponds to the endowment minus the tax payment and the penalty.

On the screen, in order to simplify decision making, a scrollbar indicates for each possible value of the reported income in between 0 and 100, the payoff if the participant is not audited and the payoff if caught cheating. At the end of each round, once all participants have validated their unique decision (the reported income) on the keyboard, a new round starts automatically. There is no feedback about actual audits and payoffs before the whole session is completed. This avoids any wealth effect during the experiment that may distort compliance behavior. At each new round, a new series of individual tax rates and audit probabilities is reassigned to the group members. The alternation of medium, low and high tax and audit regimes is intended to limit the extent of a possible inequity aversion which might influence reporting decisions.
The relatively high individual tax rate can possibly be compensated for in the next round by a lower than average rate.

The second part of the experiment also consists of 5 rounds. It corresponds to the so-called information condition (“INF” treatment). Two main changes are introduced in the protocol. The first change relates to the structure of the rounds. The second to the informational feedback. Each round now includes up to 10 periods. The idea is to allow convergence in decision making, *i.e.*, learning within the group. In the first period of a new round, new tax and audit regimes are assigned for the whole round. From the second period on, each participant receives a feedback about the group behavior in the previous period. Hence, the number of evaders among the 14 other group members and the mean reported income by the 14 other members appear on the screen. During a round, individual tax rates and audit probabilities are fixed. A new period is launched until the convergence criteria is equal to or lower than 5% in absolute value. All other parameters of the protocol remain unchanged during a round. If convergence is not achieved within 10 periods, a new round is initiated.

By combining various tax rates and audit probabilities the experiment mimics a large range of tax regimes (see Appendix B). A total of 12 sessions were carried out, each involving 10 rounds. The sessions were subdivided into 3 sets. For each one, 3 different tax and audit rates (high, medium, low) were combined differently. In all, we thus experimented with 9 tax regimes and 9 audit regimes, yielding as many as 45 individual tax and audit rates.

At the end of a session, participants were asked to fulfill an anonymous post-experimental questionnaire. This questionnaire is aimed at collecting information about individual characteristics such as the age, the gender, the college major, the number of years completed at university or college, the level of personal income and each parent’s monthly income. An additional item was added to elicit the individual degree of inequity aversion. Participants had to imagine a situation involving the share of a pie among two individuals (excluding themselves). They were asked to indicate their favorite share among two possibilities. They had to make a choice three times, successively. The alternative shares were (50,50) against (55, 65), then (50,50) against (45, 70), and finally (50,50) against (35, 85). For answering these questions participants received 1.5 Euro. Rejection of a greater but unequal payoff can be considered a signal of a high inequity aversion. The degree of inequity aversion (between 0 and 2) is included in some specifications of the model as a control variable.

This experiment was performed at GATE (Groupe d’Analyse et de Théorie Economique, France) using a Regate software. Participants were volunteer undergraduate and graduate students from four business and engineer schools and university (École Centrale, École de Management, ITECH, department of economics of the University of Lyon). Recruitment

---

11The convergence criteria is given by the difference in percentage between the average evaded amount in period $t-1$ and the average evaded amount in period $(t-2)$. 

---
was made through posters and leaflets distributed in various classes. Registration was made either by email or by phone.

A total of 180 students participated in this experiment. Since each session consisted of 10 rounds, this provides a total of 1800 observations (900 for the NOINF condition and 900 for the INF condition). Excluding rounds for which convergence was not achieved leaves a total of 795 observations for the INF condition.

At the end of the session, the average score in points accumulated throughout the session was converted at a rate of 100 points = 15 Euros. The average was preferred to the sum of points because there was no reason to pay more for a slower process of convergence to the equilibrium. Participants were paid in cash in a separate room. A show-up fee (3 Euros) was added for covering participation and the response to the questions on inequity aversion in the post-experimental questionnaire. The average earning was 13.77 Euros.

5 Econometric model

In this section, we discuss the econometric methodology used to estimate our model of tax evasion based on our experimental data. Since the model takes into consideration both exogenous and endogenous interactions, we focus exclusively on data from the second part of the experiment with feedback information. To simplify our task, a linear version of the latent equation (4) is assumed. The latter can therefore be rewritten as:

\[ D_{gik}^0 = x_{gik}^0 \beta + \gamma D_{g-ik}^0 + \bar{x}_{g-ik}^0 \delta + c^g + \eta_{gik} \]  \hspace{1cm} (8)

where \( D_{gik}^0 \) is a latent variable for the desired amount of income reported by individual \( i \) in group \( g \) at round \( k \), \( i = 1, \ldots, N \), \( g = 1, \ldots, G \), \( k = 1, \ldots, K \); \( x_{gik}^0 \) is a corresponding row vector of observable exogenous variables (including a constant term), \( \beta \) and \( \delta \) are vectors of coefficients to be estimated, \( c^g \) represents the effects of non-observable group-specific attributes which affect the intercept and \( \eta_{gik} \) is an error term capturing the effects of unobservable individual-specific attributes that may vary across rounds \( \eta_{gik} \sim N(0, \sigma^2) \). In addition, let

\[ \bar{D}_{g-ik}^0 = \frac{1}{N-1} \sum_{j=1}^{N} D_{jk}^g \quad \bar{x}_{g-ik}^0 = \frac{1}{N-1} \sum_{j=1}^{N} x_{jk}^g. \]

In this model, \( \gamma \) is the endogenous effect. If positive, it reflects a tendency to conform to the behavior of the other members of the group. When negative, participants tend to deviate

---

12 Alternatively, we could assume \( \eta_{gik} \) is the sum of a random individual effect that remains constant across the rounds of a session and a remainder random term. We did not pursue this approach in this paper.
from the group behavior. The vector $\delta$ reflects the exogenous effects (including the fairness effect). To model the correlated effects, two approaches can be used. The *group random effects* approach treats $c^g$ as a random term assuming it is orthogonal to the exogenous variables:

$$c^g_{ik} = c^g + \eta_{ik}^g.$$  

The *group fixed effects* approach allows for $c^g$ to be arbitrarily correlated with the exogenous variables. This method is more general and in fact much easier to implement than the former approach. Therefore, following Aransson et al. (1999), we have chosen to use a group fixed effects approach. There are thus $G - 1$ dummy variables to be estimated, one for each group except for an excluded group to allow identification. One can easily check for the presence of correlated effects by testing whether these coefficients are jointly equal to zero.

Following Kooreman (2003), the $N$ equations in (8) corresponding to those associated with round $k$ of session $g$ can be written in matrix notation as

$$D^{g*}_k = X^g_k \beta + \Gamma D^g_k + X^g_k \delta + C d^g \iota_N + \eta^g_k,$$

for $g = 1, \ldots, G; k = 1, \ldots, K$, (9)

where

$$\Gamma = \begin{bmatrix} 0 & \gamma & \cdots & \gamma \\ \frac{\gamma}{N-1} & 0 & \cdots & \frac{\gamma}{N-1} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\gamma}{N-1} & \frac{\gamma}{N-1} & \cdots & 0 \end{bmatrix},$$

d$^g$ is a $(G - 1)$ column vector of dummy variables and $\iota_N$ is a $N \times 1$ column vector of ones. Given that the level of reported income varies between 0 and 1, the relationship between the observed vector $D^g_k$ of reported incomes and the corresponding latent vector, is given by

$$D^g_k = I(0 < D^{g*}_i < 1)D^{g*}_i + I(D^{g*}_i \geq 1),$$

where as before $I(\cdot)$ is a vector of indicator functions which take the value one or zero. The system (9) thus corresponds to a simultaneous equation two-limit tobit with within- and cross-equation restrictions on parameters (see matrix $\Gamma$) and with error terms uncorrelated across equations. It involves both latent variables and their observed counterparts. Amemyia (1974) was the first to consider such mixed models and the approach we use to estimate our system is based on his work.

The system (9) raises two problems that must be distinguished: the coherency and the identifiability problems. The coherency (or logical consistency) problem consists in finding the condition which guarantees the system has a well-defined unique reduced form. In a general linear-in-means model, the coherency condition reduces to the invertibility of $I - \Gamma$, the matrix of coefficients of the endogenous variables. In a latent linear-in-means model with censored endogenous variables such as (9), the coherency condition is more restrictive. Amemyia (1974) has shown that every principal minor of the matrix $I - \Gamma$ must be positive. Furthermore, this coherency condition implies the existence of a unique social equilibrium at each round $k$ of session $g$. In the empirical section, this condition is checked for all specifications of the structural model.
The coherency problem logically precedes the identification problem. Indeed, the latter refers to the uniqueness of the parameters of the structural model given the parameters of the reduced form model. Identification therefore presupposes the existence of a well-defined reduced form for the endogenous variables. As discussed above, estimating social interactions models raises serious identification problems. In our approach, results from Manski (1993) imply that it is impossible to identify the structural parameters $\beta, \gamma, \delta$ and $c^g$ ($g = 1, \ldots, G - 1$) when the model involves no censored endogenous variables ($D^g_{ki} = D^g_{ki}$ for all $i, k$ and $g$) and without a priori restrictions on the parameters of $\delta$. The reason (Moffitt 2001) is that the order condition for identification in a structural linear model is not satisfied. In the linear-in-means model, this condition requires that at least one exogenous social interaction effect is excluded from the equations.

In theory, models with endogenous censored variables as in (9) may be easier to identify. Indeed, given the nonlinear (more precisely, piecewise linear) relationship between observed reported income and the corresponding latent variable, the model imposes a nonlinear relationship between the individual behavior and the mean behavior of the reference group. As emphasized by Brock and Durlauf (2001b), this is likely to resolve the identification problem since identification is a generic property of nonlinear models with self-consistency beliefs (which apply in our case since only observations at the social equilibrium are used). From the econometric point of view, this result is consistent with the idea that nonlinearity generally helps rather than hampers identification. However, it is important to note that identification hinges on knowing the specific form of nonlinearity which, in our model, depends on the assumption of normality of the error terms. In the following, we will not derive formally the conditions for identification in our model. Rather, we test the identification of the model by estimating its most general version (i.e., with no excluded social effects) while ensuring that the likelihood function converges to a unique maximum.

To derive the likelihood function of our model, define $Z^g_{ik} = (x^g_{ik}, D^g_{-ik}, x^g_{-ik}, 1)$ and $\alpha = (\beta, \gamma, \delta, c^g)'$ so that, from (8), one has: $D^g_{ik} = Z^g_{ik} \alpha + \eta^g_{ik}$. Now, for any given round $k$ in session $g$ define:

- $X^g_k$ : the number of players who reported $0 < D^g_{ik} < 1$,
- $Y^g_k$ : the number of players who reported $D^g_{ik} = 0$,
- $Z^g_k$ : the number of players who reported $D^g_{ik} = 1$.

Note that these numbers must satisfy: $X^g_k + Y^g_k + Z^g_k = N$.

---

13 These authors derive conditions for identification in the case of a discrete-choice generalized logistic model of social interactions and show that they are much less restrictive than for the linear-in-means model. However, they do not analyze the case of a mixed discrete-continuous tobit-type model such as the one used in this paper.
Now divide the observations on rounds (for \( k = 1, \ldots, K \) and \( g = 1, \ldots, G \)) into seven subsets:

\[
\begin{align*}
S_1 & : X^g_k > 0, Y^g_k = 0, Z^g_k = 0. \\
S_2 & : X^g_k > 0, Y^g_k > 0, Z^g_k = 0. \\
S_3 & : X^g_k > 0, Y^g_k = 0, Z^g_k > 0. \\
S_4 & : X^g_k > 0, Y^g_k > 0, Z^g_k > 0. \\
S_5 & : X^g_k = 0, Y^g_k > 0, Z^g_k = 0. \\
S_6 & : X^g_k = 0, Y^g_k = 0, Z^g_k > 0. \\
S_7 & : X^g_k = 0, Y^g_k > 0, Z^g_k > 0.
\end{align*}
\]

Then, denoting the standard normal density and cumulative functions of \( \eta^g_{ik} \) by \( f(\eta^g_{ik}) \) and \( F(\eta^g_{ik}) \) respectively, the likelihood function of the model (8) is given by:

\[
L = \prod_{S_1} |B_N| \left[ \prod_{S_2} f(D^g_{ik} - Z^g_{ik}\alpha) \right] \times \prod_{S_2} \left[ \prod_{X^g_k} B_{X^g_k} f(D^g_{ik} - Z^g_{ik}\alpha) \prod_{Y^g_k} F(-Z^g_{ik}\alpha) \prod_{Z^g_k} F(Z^g_{ik}\alpha - 1) \right] \times \prod_{S_3} \left[ \prod_{X^g_k} B_{X^g_k} f(D^g_{ik} - Z^g_{ik}\alpha) \prod_{Y^g_k} F(-Z^g_{ik}\alpha) \prod_{Z^g_k} F(Z^g_{ik}\alpha - 1) \right] \times \prod_{S_5} \left[ \prod_{Y^g_k} F(-Z^g_{ik}\alpha) \prod_{Z^g_k} F(Z^g_{ik}\alpha - 1) \right] \times \prod_{S_6} \left[ \prod_{Y^g_k} F(Z^g_{ik}\alpha - 1) \right] \times \prod_{S_7} \left[ \prod_{Y^g_k} F(-Z^g_{ik}\alpha) \prod_{Z^g_k} F(Z^g_{ik}\alpha - 1) \right],
\]
with

\[ B_{X_k} = \begin{vmatrix} 1 & -\frac{\gamma}{N-1} & \cdots & -\frac{\gamma}{N-1} \\ -\frac{\gamma}{N-1} & 1 & \cdots & -\frac{\gamma}{N-1} \\ \vdots & \vdots & \ddots & \vdots \\ -\frac{\gamma}{N-1} & -\frac{\gamma}{N-1} & \cdots & 1 \end{vmatrix}, \]

the determinant of the corresponding matrix \( [X_k^g \times X_k^g] \). Maximizing the log of (10) with respect to \( \alpha \) and \( \sigma \) yields the full information maximum likelihood estimates of the model. Under standard regularity assumptions, these estimates are consistent and asymptotically efficient.

### 6 Results

Table 1 provides descriptive statistics for our sample. Note that most subjects are young (23.6 years old on average with a standard deviation of 5.9). Also 60% of them are male. Both tax rates and audit probabilities display a large standard deviation (see also Appendix B). This helps to identify their impact on tax compliance behavior. Over 88% (53/60) of all rounds with feedback information on the tax compliance satisfy the convergence criterion and therefore correspond to a social equilibrium. This leaves us with 795 observations on individual reported amounts in part II of the experiment (INF treatment) over a potential of 900 observations. In the INF treatment, a percentage of 24.5% of these observations (195) are censored at zero while a percentage of 19% (151 observations) are censored at 100 for a total of 43.5% censored observations (346). The corresponding percentages in the NOINF treatments are 18% (164 observations), 21% (189 observations) and 39% (353). In the INF treatment, the average amount reported (50.15) is about half of the amount received by an individual at each period and it is slightly lower than the average reported income in the treatment without any feedback (53.92).

Figures 1 and 2 compare the average reported income with and without group information, respectively, and according to individual tax rates and audit probabilities. Figure 1 shows reported income slightly increasing with individual tax rates, except for the rates beyond 60%. Figure 2 shows that the reported income increases mostly as a function of individual audit probabilities. The comparison of the reported incomes with and without feedback information shows that for a large majority of tax rates and audit probabilities, the reported income is lower when participants are provided feedback information on the number of tax evaders and the average reported income. However, these unconditional statistics need to be interpreted with care as they do not take into account other variables that have a direct effect on reported income.
Table 2 reports detailed estimation results for various specifications of the model. Columns (1) and (2) provide results for the most general specification. The latter corresponds to a full linear-in-means model (but with censored variables) since all mean group variables which are analogous to individual characteristics variables included in the model are included. Therefore, there are no exclusion restrictions on exogenous interactions variables. Also, correlated effects are taken into account through 11 group dummies. Note that the tax rate variable, $t_i$, is entered nonlinearly since our model predicts that its impact on tax compliance can be decomposed into the sum of two effects with opposite signs. Moreover, the squared term is significant at the 10% level. Only one individual characteristics variable (gender dummy) has been included in this specification since no other individual variable was significant at the 10% level.

Columns (1) provide the estimation results for the general specification but using a simple two-limit tobit. It thus ignores the possible simultaneity bias. Recall that this bias may arise from the fact that not only an individual’s behavior is influenced by the behavior of others but the behavior of others is influenced by an individual’s behavior. Moffitt (2001) and Krauth (2002) insisted on the potential importance of this bias when the number of individuals in the reference group is small (the endogeneity bias tends to zero when the group increases to infinity). Since there are only 15 participants in a session, this phenomenon may significantly bias the estimate of the endogenous social effect.

Results from columns (1) show that, unexpectedly, the coefficient associated with $D_{-i}$ is negative and significant at the 5% level. The marginal effect of this variable (not reported in the table)\(^{14}\) is significant and is equal to -1.83. This indicates that an increase in the mean group’s tax evasion encourages individuals to reduce tax evasion. This is contrary to what is expected in the presence of a social conformity effect. There are four reasons why such a result may obtain. First, tax evasion behavior may induce a social anti-conformity rather than a social conformity effect. In other words, on average, participants have an inclination to adopt a behavior that deviates from that of their group. Kooreman (2003) obtains such an anti-conformity effect in the case of self-esteem of students in a same class. More precisely, he finds that the self-esteem of a student increases at the expense of the self-esteem of others in the class. However, the coefficient was not significant. In our tax evasion experiment, it is unlikely that social anti-conformity explains the negative coefficient, even if this kind of behavior could prevail for a small number of individuals.

A second interpretation is that an individual decides to reduce his tax evasion when his group evades more in order to prevent a too important decline in the level of public goods funded by taxes. In our model, this would require public goods not to be separable from private

\(^{14}\)Estimates of the marginal effects for all specifications of Table 2 are forthcoming. The complexity of estimating these effects when using a two-limit simultaneous tobit prevented us from reporting them in this version of the paper.
consumption in the utility function. This explanation may be contested since participants were informed that the taxes raised would be invested in scientific research and not on a program directly related to their own interest.

A third interpretation is that an individual reduces his tax evasion when his group evades more because he becomes underconfident and fears a change in audit motivated by a too high level of fraud. This explanation may be contested since audit regimes are exogenous.

Finally, a last possibility is that the use of a simple two-limit tobit induces a bias in the estimated coefficient of $D_{-i}$ since this method does not take into account the endogeneity of this variable. To verify this, we estimate the same model but this time allowing for the endogeneity of $D_{-i}$. Of course, in this absence of any censored variables and no exclusion restrictions, it would not be possible to estimate this model consistently since it is unidentified. However, with censored variables and under normality of the error terms, the model becomes identified. Results are reported in columns (2). Note first that the model estimated in this specification and in all other specifications using a two-limit simultaneous tobit is coherent since the principal minors of the matrix $I - \Gamma$ are positive in all cases. The coefficient of $D_{-i}$, while still negative, is now much smaller (-0.046 rather than -2.936) and is no longer significant ($t = 1.02$). This result indicates that there is no endogenous interactions effects in our experiment. This result is robust to changes in model specification since, in all other specifications reported in Table 2, the coefficient of $D_{-i}$ is not significant when this variable appears as a regressor. In short, the social multiplier is equal to one in our experiment.

One must be cautious before concluding from our empirical analysis that tax evasion behavior does not in general generate any endogenous interactions effects. Indeed, there is survey evidence showing that individual compliance is dependent on the perception of aggregate compliance, guilt and shame (stigma) from non compliance being smoothed when others are also cheating the government (Sheffrin and Triest 1992). Also, some experimental evidence indicates that the decision to comply is influenced by moral considerations and tax morale (Torgler 2002), and not only by the expected returns of evasion (Baldry, 1986). The role of social customs has also been indirectly documented by replicating the same experiments in various countries. Other things being equal, if American subjects evade less than the Spanish do (Alm et al. 1995), and Albanian subjects less than the Dutch do (Gërxhani and Schram, 2002), it suggests that the societal attitudes, social norms of compliance influence individual behavior (Cummings et al. 2001).

To test for the presence of exogenous interactions effects, we have shown (see equation (4)) that it is convenient to estimate the model with the tax and audit probability variables introduced not only at the individual level ($t_i$ and $p_i$) but also in difference with the corresponding mean group variables ($t_{-i} - \bar{t}_i$ and $p_{-i} - \bar{p}_i$). Since the mean group squared tax variable ($t_{-i}^2$) is not significant in specification (2), we have excluded it in specification (3) to
ease the interpretation of the coefficients. In specification (3), the coefficient of the variable \( t_i - \bar{t}_{-i} \) is negative and significant at the 5% level. This suggests the presence of a fairness effect with respect to taxation. In other words, when the difference between an individual’s tax rate and that of the others increases, he reports less income in order to restore fiscal equity amongst the participants. This result is consistent with some experimental evidence according to which perceived relative tax burden influences reporting behavior. In particular, Spicer and Becker (1980) found that individuals who were told their taxes were higher than others reported relatively small amounts.\(^{15}\) On the other hand, the coefficient associated with \( p_i - \bar{p}_{-i} \) is not significantly different from zero. This suggests the absence of fairness effect related to the fraud preventing policy.

Our results indicate that, at the mean tax rate (= 0.38), the positive effect of a change in the tax rate on tax compliance (Yitzhaki’s prediction) dominates. Indeed, coefficients associated with \( t_i \) and \( t_i^2 \) in columns (3) indicate that at this tax rate level, a one percentage increase in an individual’s tax rate increases his desired reported income by 0.622. Note however that our results also predict that the positive impact of the tax rate on reporting behavior appears only for tax rates over 0.21. Below that level, an increase in the tax rate encourages tax evasion. In this case, the negative effect dominates. As discussed above, both positive and negative effects are consistent with our model when there is a positive social marginal utility associated with tax compliance. Interestingly, the experimental results on the influence of tax rates on compliance are also not clear cut. In some studies, an increased tax rate decreases compliance (Friedland et al. 1978; Collins and Plumlee 1991); in others, the correlation is positive (Beck et al. 1991; Alm et al. 1995).

Columns (3) also provide results that are consistent with the Alingham-Sandmo proposition according to which an increase in the audit probability reduces tax evasion. The coefficient associated with \( p_i \) (= 1.605) is positive and significant at the 5% level. This is consistent with empirical evidence according to which an increase in audit rates increases tax compliance (Friedland et al. 1978; Beck et al. 1991, Slemrod et al. 2001). Moreover, results presented in columns (3) confirm empirical evidence according to which women evade less than men (Spicer and Becker 1980; Baldry 1986; Gérxhani and Schram, 2002). The coefficient associated with the gender variable indicates that, ceteris paribus, females report 17.6 units more income than males.

As far as correlated effects are concerned, only one group dummy \( (g_9) \) is significant at the 10% level. To test the absence of correlated effects (due to sorting biases or common shocks within groups), we re-estimated the model with no group dummies. Results are provided in columns (4). A likelihood ratio test based on columns (3) and (4) cannot reject that all group dummies are zero (statistic=13.5 as compared with a critical statistic of \( \chi^2(11, .05) = 19.68 \)).

\(^{15}\)However, Webley et al. (1991) found no fairness effect in an experiment similar to that of Spicer and Becker, rejecting equity as an important aspect for the extent of tax compliance.
Our results are thus consistent with a fully randomized sample. Note however that the mean group gender variable \((\text{sex}_{i})\) is now significant at the 5% level, which indicates the presence of a correlation between this variable and group dummies.

Columns (5) provide estimation results where both endogenous effects and correlated effects are assumed away.\(^{16}\) Interestingly, the fairness effect on taxation is still significant at the 10% level and its value is close to the one obtained when both endogenous effects and correlated effects are included in the model (see columns (3)). This result thus confirms the presence of exogenous effects in our experiment. Finally, column (6) introduces our inequity aversion index \((\text{avers}_{i})\) and its average group counterpart into the model. As expected, its coefficient is positive and significant at the 5% level, thus indicating that those individuals with a high inequity aversion are likely to evade less, \textit{ceteris paribus}. However, introducing this variable has no impact on the other coefficients of the model.\(^{17}\)

7 Summary and extensions

Research on tax evasion behavior usually ignores “peer effects” or “social interactions effects”. This omission is due to the fact that testing for such effects is notoriously difficult for two basic reasons. First, outcomes data rarely reveal the reference group composition, whether it is the family, the parish or work colleagues. Even when the group composition is known, estimating interaction-based models raises severe identification problems.

In this paper we have shown that an experimental approach can be useful in resolving these problems. Reference groups are naturally defined by subjects present in the laboratory in each session. Moreover, the presence of censored data (no tax compliance or full tax compliance) implies that individual behavior varies in a specific nonlinear manner with the mean group behavior, assuming normality of the error terms. This nonlinearity allows identification of the model without the need to impose identifying restrictions.

Consistent with the recent empirical literature on social interactions, our paper also shows that the estimation method is crucial to obtain consistent estimates of interactions effects. Thus, when we ignore the simultaneity bias arising from the fact that mean group behavior is itself influenced by individual behavior, our estimation results indicate the presence of a strong social anti-conformity effect. This effect completely disappears when the simultaneity

\(^{16}\)Testing this restriction from a test based on the log likelihood statistics of columns (3) and (5) is incorrect since the simple two limit tobit is not nested into our two-limit simultaneous tobit.

\(^{17}\)We also test for the presence of a dynamic behavior by introducing a dummy for each round (except the first one) in the model. These dummies were never significant at the 5% level.
problem is taken into account using an appropriate estimation method (two-limit simultaneous tobit).

Our results indicate the presence of a fairness effect relative to taxation. Those individuals whose tax rate is higher than their mean group tax rate (for a given level of income) tend to evade more in order to restore equity in taxation. This suggests that perceived unfair taxation encourages tax evasion. At the policy level, this means that a taxation system that is more equitable both horizontally and vertically is likely to improve tax compliance.

As noted by a number of researchers (e.g., Manski 2000), experimental research has also its own limitations. Thus, in our experiment, the groups of taxpayers in the laboratory are formed artificially for the sake of the experiment. Thus one has to be cautious when extrapolating our findings to the population of taxpayers even though the literature on subject-pool effects tend to support the external validity of experiments when there is no framing effect.

These limitations suggest a number of avenues for further research. First, it is often argued that a random selection of subjects makes the experiments more credible. The robustness of our findings could be investigated with respect to a full randomization of participants (in our experiment, they were volunteer undergraduate and graduate students). Another avenue of research is the analysis of the impact of the group size on the importance of interactions effects. It would also be interesting to test for social learning effects (for example, only a fraction of the subjects would be informed on the audit probability). At the econometric level, one could estimate a structural model of tax evasion with social interactions using a functional form for the utility function. Finally, the expected utility model used in this paper could also be tested with respect to other uncertainty models of tax evasion.
References


Appendix A Instructions

You will be participating in an experiment on decision in economics supported by both the University Laval in Quebec and the University Lumière Lyon 2. During this session, you can earn money and the amount of your earnings depend on your decisions.

This session consists of 10 rounds. The five first rounds are single-period and each of the five further rounds include several periods. During each period, you will obtain a score in points. The average score in points accumulated throughout the session will determine your earnings. Points are converted into Euros at the following rate:

100 points = Euros 15

In addition, you will receive a show-up fee of Euro 1.5. Your earnings in Euros will be paid to you in cash at the end of the session in a separate room in order to preserve the confidentiality of your earnings.

During this session, you belong to a group of 15 participants from the same school. All your decisions will remain anonymous. Throughout the entire session, talking is not allowed. Any violation of this rule will result in being excluded from the session and not receiving payment. If you have any questions regarding these instructions, please raise your hand; your question will be answered publicly.

ROUNDS 1 to 5

Content of each round

Each of these 5 rounds consists of a single period.

At the beginning of each round, each member of the group receives an endowment of 100 points. You are requested to give back a percentage of this endowment that we call "rate of deduction". There are 5 different rates applied in the group and each of these rates is randomly assigned to 3 participants. The sum of the deductions from the group members serves to fund scientific projects.

In order to fulfill this request, you have to report, by means of a scrollbar, an amount in between 0 and 100 (100 corresponding to the endowment that you received). Your deduction rate will apply to your reported amount.

This amount can be audited according to a certain audit probability and this audit may entail a penalty. There are 5 different audit probabilities in the group and each of these probabilities is randomly assigned to 3 participants. The consequences of an audit are indicated below. There are 3 possible cases.

* If the amount that you have reported is not audited, your deduction rate will apply to your reported amount. Indeed, in this context, no penalty applies. Your payoff is given by the following formula:

Payoff = endowment - deduction
deduction = deduction rate * reported amount

* If the amount that you have reported is audited and if it is equal to your endowment, your deduction rate applies to this amount and consequently no penalty applies. Your payoff is given by the following formula:

\[ \text{Payoff} = \text{endowment} - \text{deduction} \]

where \( \text{deduction} = \text{deduction rate} \times \text{endowment} \)

* If the amount that you have reported is audited and if it is lower than your endowment, your deduction rate applies to your endowment. In addition, a penalty should be paid that consists of applying your deduction rate to the non reported fraction of your endowment. Then, your payoff is given by the following formula:

\[ \text{Payoff} = \text{endowment} - \text{deduction} - \text{penalty} \]

with \( \text{deduction} = \text{deduction rate} \times \text{endowment} \)

and \( \text{penalty} = \text{deduction rate} \times (\text{endowment} - \text{reported amount}) \)

**Which information do you receive at the beginning of each round?**

At the beginning of each round, you are informed about the following elements:

- the 5 different deduction rates in the group
- your own deduction rate
- the 5 different audit probabilities in the group
- your own audit probability.

On your computer screen, there is a scrollbar, graduated from 0 to 100, with which you can indicate your reported amount. When you move this scrollbar, you can observe, for your information, both your payoff if you are audited and your payoff if you are not audited, for each possible reported amount. To validate your decision, you must stop the scrollbar on the amount that you decide to report, then you must click the OK button. As soon as all the members of the group will have clicked the OK button, the next round will begin automatically.

You will be informed of the following elements regarding each round only at the end of the session:

- the actual audit of your reported amounts and the number of the periods where an audit took place,
- the payment of a penalty when applicable,
- your actual payoff.

**What does change from a round to another one?**

30
Each round is independent from the others.

At the beginning of each new round, you will receive a new endowment of 100 points.

In each new round, new deduction rates and new audit probabilities are applied in the group. Thus, you may be assigned randomly a new deduction rate and a new audit probability.

[The following instructions were distributed to the participants after round 5 was completed].

**ROUNDS 6 to 10**

The session will continue right now, however with two changes.

1) From now on, each round consists of several periods.

   At the beginning of each new period in a round, you will receive an endowment of 100 points. For the whole periods of the same round, everybody keeps the same deduction rate and the same audit probability. In contrast, when a new round begins, new deduction rates and audit probabilities will be applied in the group and to you in particular.

2) From the beginning of the second period of a round on, you will be given two additional pieces of information:

   - how many members, among the 14 other group members, have reported less than their endowment in the preceding period
   - the average amount reported by the 14 other group members in the preceding period.
Appendix B Values of tax rates and audit probabilities

The values of the tax rates and the audit probabilities used in each session are the following:

1) Values for sessions 1 to 4

Distribution of the audit probabilities

<table>
<thead>
<tr>
<th>Regime</th>
<th>Individual Probability</th>
<th>Mean</th>
<th>Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.04 0.08 0.11 0.33 0.37</td>
<td>0.18</td>
<td>12.2</td>
</tr>
<tr>
<td>Medium</td>
<td>0.07 0.22 0.27 0.32 0.37</td>
<td>0.25</td>
<td>10.3</td>
</tr>
<tr>
<td>High</td>
<td>0.24 0.27 0.33 0.37 0.43</td>
<td>0.33</td>
<td>6.2</td>
</tr>
</tbody>
</table>

Distribution of the tax rates

<table>
<thead>
<tr>
<th>Regime</th>
<th>Individual tax rates</th>
<th>Mean</th>
<th>Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.05 0.10 0.15 0.30 0.70</td>
<td>0.26</td>
<td>23.5</td>
</tr>
<tr>
<td>Medium</td>
<td>0.20 0.35 0.40 0.50 0.55</td>
<td>0.40</td>
<td>12</td>
</tr>
<tr>
<td>High</td>
<td>0.40 0.45 0.50 0.55 0.60</td>
<td>0.50</td>
<td>7</td>
</tr>
</tbody>
</table>
2) Values for sessions 5 to 8

### Distribution of the audit probabilities

<table>
<thead>
<tr>
<th>Regime</th>
<th>Individual Probability</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.08 0.12 0.15 0.37 0.41</td>
<td>0.23</td>
<td>13.6</td>
</tr>
<tr>
<td>Medium</td>
<td>0.13 0.27 0.32 0.37 0.42</td>
<td>0.30</td>
<td>9.95</td>
</tr>
<tr>
<td>High</td>
<td>0.28 0.30 0.37 0.40 0.47</td>
<td>0.36</td>
<td>6.89</td>
</tr>
</tbody>
</table>

### Distribution of the tax rates

<table>
<thead>
<tr>
<th>Regime</th>
<th>Individual tax rates</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.10 0.15 0.20 0.35 0.75</td>
<td>0.31</td>
<td>23.54</td>
</tr>
<tr>
<td>Medium</td>
<td>0.25 0.40 0.45 0.55 0.60</td>
<td>0.45</td>
<td>12.25</td>
</tr>
<tr>
<td>High</td>
<td>0.45 0.50 0.55 0.60 0.65</td>
<td>0.55</td>
<td>7.07</td>
</tr>
</tbody>
</table>

3) Values for sessions 9 to 12

### Distribution of the audit probabilities

<table>
<thead>
<tr>
<th>Regime</th>
<th>Individual Probability</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.02 0.04 0.07 0.29 0.33</td>
<td>0.15</td>
<td>13.22</td>
</tr>
<tr>
<td>Medium</td>
<td>0.03 0.18 0.23 0.28 0.33</td>
<td>0.21</td>
<td>10.29</td>
</tr>
<tr>
<td>High</td>
<td>0.20 0.23 0.29 0.33 0.40</td>
<td>0.29</td>
<td>7.13</td>
</tr>
</tbody>
</table>

### Distribution of the tax rates

<table>
<thead>
<tr>
<th>Regime</th>
<th>Individual tax rates</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.05 0.10 0.15 0.25 0.65</td>
<td>0.24</td>
<td>21.54</td>
</tr>
<tr>
<td>Medium</td>
<td>0.15 0.30 0.35 0.45 0.50</td>
<td>0.35</td>
<td>12.25</td>
</tr>
<tr>
<td>High</td>
<td>0.35 0.40 0.45 0.50 0.55</td>
<td>0.45</td>
<td>7.07</td>
</tr>
</tbody>
</table>
Table 1
Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Stand. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amount reported in Part I</td>
<td>53.92</td>
<td>37.54</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Amount reported in Part II</td>
<td>50.15</td>
<td>38.68</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Age</td>
<td>23.61</td>
<td>5.94</td>
<td>17</td>
<td>50</td>
</tr>
<tr>
<td>Tax rate</td>
<td>0.38</td>
<td>0.16</td>
<td>0.05</td>
<td>0.75</td>
</tr>
<tr>
<td>Audit probability</td>
<td>0.25</td>
<td>0.11</td>
<td>0.02</td>
<td>0.47</td>
</tr>
<tr>
<td>Sex (Female=1)</td>
<td>0.40</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Inequality aversion index</td>
<td>1.33</td>
<td>0.84</td>
<td>0</td>
<td>2</td>
</tr>
</tbody>
</table>

Number of observations

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Groups</td>
<td>12</td>
</tr>
<tr>
<td>Rounds Part I + Part II</td>
<td>120</td>
</tr>
<tr>
<td>Rounds that converged in Part II</td>
<td>53</td>
</tr>
<tr>
<td>Participants per group</td>
<td>15</td>
</tr>
<tr>
<td>Observations on amount reported in Part I</td>
<td>900</td>
</tr>
<tr>
<td>Observations on amount reported in Part II*</td>
<td>795</td>
</tr>
<tr>
<td>- Censored at 0 in Part I (Part II)</td>
<td>164 (195)</td>
</tr>
<tr>
<td>- Censored at 100 in Part I (Part II)</td>
<td>189 (151)</td>
</tr>
<tr>
<td>- Not censored in Part I (Part II)</td>
<td>547 (449)</td>
</tr>
</tbody>
</table>

* Observations are limited to games that converged.
## Table 2

*Estimation results of the structural form model of tax compliance*

(Independent variable: Reported Individual divided by 100: $D_i/100$)

<table>
<thead>
<tr>
<th></th>
<th>(1) two limit tobit</th>
<th>(2) two limit simultaneous</th>
<th>(3) two limit simultaneous</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.380</td>
<td>5.032</td>
<td>-0.109</td>
</tr>
<tr>
<td>$t_{i-1}$</td>
<td>-1.381</td>
<td>0.781</td>
<td>-1.874</td>
</tr>
<tr>
<td>$t_{i-2}$</td>
<td>1.774</td>
<td>0.985</td>
<td>2.323</td>
</tr>
<tr>
<td>$p_{i-1}$</td>
<td>1.767</td>
<td>0.224</td>
<td>1.575</td>
</tr>
<tr>
<td>$\overline{t}_{-i}$</td>
<td>2.818</td>
<td>1.263</td>
<td>2.126</td>
</tr>
<tr>
<td>$\overline{p}_{-i}$</td>
<td>-2.522</td>
<td>1.918</td>
<td>-2.353</td>
</tr>
<tr>
<td>$t_i - \overline{t}_{-i}$</td>
<td>2.434</td>
<td>0.710</td>
<td></td>
</tr>
<tr>
<td>$p_i - \overline{p}_{-i}$</td>
<td></td>
<td></td>
<td>0.294</td>
</tr>
<tr>
<td>$\overline{D}_{-i}$</td>
<td>-2.936</td>
<td>0.409</td>
<td>-0.046</td>
</tr>
<tr>
<td>sex$_i$($female = 1$)</td>
<td>0.128</td>
<td>0.631</td>
<td>0.171</td>
</tr>
<tr>
<td>sex$_{-i}$</td>
<td>0.358</td>
<td>8.782</td>
<td>0.006</td>
</tr>
<tr>
<td>$g_1$</td>
<td>0.525</td>
<td>0.583</td>
<td>0.167</td>
</tr>
<tr>
<td>$g_2$</td>
<td>0.235</td>
<td>1.824</td>
<td>0.086</td>
</tr>
<tr>
<td>$g_3$</td>
<td>0.102</td>
<td>0.703</td>
<td>0.025</td>
</tr>
<tr>
<td>$g_4$</td>
<td>0.004</td>
<td>0.486</td>
<td>-0.037</td>
</tr>
<tr>
<td>$g_5$</td>
<td>0.113</td>
<td>3.690</td>
<td>0.021</td>
</tr>
<tr>
<td>$g_6$</td>
<td>-0.339</td>
<td>4.310</td>
<td>-0.139</td>
</tr>
<tr>
<td>$g_7$</td>
<td>-0.182</td>
<td>3.059</td>
<td>-0.101</td>
</tr>
<tr>
<td>$g_8$</td>
<td>0.149</td>
<td>1.815</td>
<td>0.062</td>
</tr>
<tr>
<td>$g_9$</td>
<td>0.598</td>
<td>0.682</td>
<td>0.219</td>
</tr>
<tr>
<td>$g_{10}$</td>
<td>0.348</td>
<td>1.210</td>
<td>0.109</td>
</tr>
<tr>
<td>$g_{11}$</td>
<td>0.387</td>
<td>1.933</td>
<td>0.108</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.627</td>
<td>0.023</td>
<td>0.581</td>
</tr>
<tr>
<td>Log Lik.</td>
<td>-742.835</td>
<td></td>
<td>-720.829</td>
</tr>
</tbody>
</table>

Number of observations: 795
Table 2
Estimation results of
the structural form model of tax compliance
(continued)
(Dependent variable: Reported individual income divided by 100: $D_i/100$)

<table>
<thead>
<tr>
<th></th>
<th>(4) two limit simultaneous tobit</th>
<th>(5) two limit tobit</th>
<th>(6) two limit tobit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Constant$</td>
<td>-0.071</td>
<td>0.212</td>
<td>0.090</td>
</tr>
<tr>
<td>$t_i$</td>
<td>-0.742</td>
<td>0.586</td>
<td>-0.351</td>
</tr>
<tr>
<td>$t_i^2$</td>
<td>1.590</td>
<td>0.826</td>
<td>1.267</td>
</tr>
<tr>
<td>$p_i$</td>
<td>1.368</td>
<td>0.520</td>
<td>1.256</td>
</tr>
<tr>
<td>$t_i - \bar{t}_{-i}$</td>
<td>-0.542</td>
<td>0.346</td>
<td>-0.654</td>
</tr>
<tr>
<td>$p_i - \bar{p}_{-i}$</td>
<td>0.523</td>
<td>0.524</td>
<td>0.556</td>
</tr>
<tr>
<td>$D_{-i}$</td>
<td>-0.028</td>
<td>0.054</td>
<td></td>
</tr>
<tr>
<td>$Avers_i$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Avers_{-i}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$sex_i (female = 1)$</td>
<td>0.195</td>
<td>0.047</td>
<td>0.161</td>
</tr>
<tr>
<td>$sex_{-i}$</td>
<td>0.344</td>
<td>0.149</td>
<td>0.485</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.589</td>
<td>0.022</td>
<td>0.657</td>
</tr>
<tr>
<td>Log Lik.</td>
<td>-728.490</td>
<td></td>
<td>-775.664</td>
</tr>
</tbody>
</table>

Number of observations: 795
Fig. 1. Distribution of average reported income by tax rate and information condition

Fig. 2. Distribution of average reported income by audit probability and information condition