AN AGENT-BASED MODEL OF TAX COMPLIANCE: AN APPLICATION TO THE SPANISH CASE

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We present a new agent-based model for the simulation of tax compliance and tax evasion behaviour (SIMULFIS). The main novelties of the model are the introduction of a ‘behavioural filter approach’ to model tax decisions, the combination of a set of different mechanisms to produce tax compliance (namely rational choice, normative commitments, and social influence), and the use of the concept of ‘fraud opportunity use rate’ (FOUR) as the main behavioural outcome. After describing the model in detail, we display the main behavioural and economic results of 1,920 simulations calibrated for the Spanish case and designed to test for the internal validity of SIMULFIS. The behavioural outcomes show that scenarios with strict rational agents strongly overestimate tax evasion, while the introduction of social influence and normative commitments allows to generate more plausible compliance levels under certain deterrence conditions. Interestingly, the relative effect of social influence is shown to be ambivalent: it optimizes compliance under low and middle deterrence conditions, but not when deterrence is made harder. Finally, SIMULFIS economic outcomes are broadly in line with theoretical expectations,
thus supporting the reliability of the model.

Keywords: Rational choice; social influence; tax behaviour; tax evasion; tax morale.

1. Presentation and Purpose of SIMULFIS

Tax evasion, usually defined as the voluntary reduction of the tax burden by illegal means [29], is a problem of huge social relevance at present times. a This is so, first, because tax evasion reduces the volume of resources available for the public sector. This reduction is specially damaging in the Spanish case, where different authors estimate that the shadow economy represents around 20% of the Spanish GNPb. Second, since tax evasion behaviour is not equally distributed among taxpayers, it violates the principles of fairness, equality, and progressivity that the tax system ought to satisfy.c

Academic researchers who aim to explain tax evasion and tax compliance are increasingly acknowledging the need to include psychological, social, and cultural factors in their explanatory models; traditional explanations were too often linked to the strict assumptions of rational choice theory and the homo oeconomicus model [2]. Instead, new studies focus, for example, on taxpayers’ tax morale (their tolerance towards tax fraud [61]). Recently, it has been shown that there is a causal link between aggregated tax morale and the volume of the shadow economy at the national level [36]; at the individual level, some contributions have proved the relationship between individual tax morale and self-declared levels of tax evasion [19, 24, 62], as well as tax non-compliance behaviour in the laboratory [43]. Besides tax morale, factors such as social norms, social influence, fairness concerns, and perceptions of the distributive outcomes of the tax system are increasingly taken as likely determinants of tax compliance [5, 20, 39, 41, 42, 50].

There is little doubt that the understanding of the causes and determinant factors of the variations of tax evasion levels across time and space is a pressing need in the present context of economic crisis and scarcity of public resources. Such an understanding would help to design robust institutional strategies and policies in order to tackle tax evasion and, therefore, improve the efficacy and fairness of the tax system. Besides, reducing tax evasion allows increasing public resources without need to raise tax rates. This is especially interesting when one looks at the difficulties that governments face today in order to achieve public budget equilibrium and fund welfare programs.

The SIMULFIS project is conceived as the first stone of a research strategy to fill three gaps in contemporary research on tax evasion:

aWe will take the expressions ‘tax evasion’ and ‘tax fraud’ as equivalent for our purposes, though they might have slightly different meanings in part of the literature on tax compliance.
bArrazola [12] estimates that Spanish shadow economy represents approximately 17% of GNP; GESTHA [32] estimates a higher 23.3% (http://www.gestha.es/?seccion=actualidad&num=104).
cA useful presentation of the normative principles that guide tax systems and of their relationship with ethical theory may be found in [7].
Theoretically, most of the studies on tax compliance deal separately with different factors which hypothetically affect tax behaviour. On the contrary, SIMULFIS seeks to integrate different mechanisms which have been tested in isolation by previous research, in order to make them interact in a complex computational setting. Thus, SIMULFIS aims to test the consistency and acceptability of different theoretical hypothesis proposed in the literature on tax compliance. Specifically, the model includes the possibility of interactions between the three main types of mechanisms which have been considered by the literature as likely determinants of tax evasion decisions: rational choice (or utility maximization), fairness concerns, and social influence. To study this interaction through a virtual agent-based model is the main theoretical motivation of the project.

Methodologically, the use of agent-based models allow to overcome one of the most important shortcomings of standard economic models of tax evasion: the huge difficulty to simulate complex social dynamics in a realistic way while keeping at the same time mathematical tractability. Agent-based methodology allows to build more realistic models where, for example, each agent may have specific individual properties, and social interaction may be properly modelled.

Politically, once the model is properly calibrated and validated, it is likely to become a useful tool (though complementary of others) in order to assess existing tax policies as well as their possible reforms, by providing virtual outcomes on their direct and indirect behavioural and economic effects. As an example, in this paper we present the first results of an empirical calibration of the model for the Spanish case.

2. Previous Research on Tax Evasion Modelling

The first economic models of tax evasion were presented four decades ago by Allingham and Sandmo [2] and Srinivasan [57]. Those neoclassical economic models adapted Gary Becker’s ‘crime economics’ to the study of tax behaviour. The aim was to explain deviant behaviour (in this case, tax evasion) as rational choice: each taxpayer decides how much of her income she declares as a function of the benefits of concealing it (given a tax rate) and the costs of being caught (given a probability of being audited and the amount of the fine). Research on tax evasion in the last two decades can be depicted as a series of consecutive attempts to broaden the traditional neoclassical economic model in order to explain an action (tax compliance) which appears to be ‘almost-voluntary’ [45].

It is not surprising, then, that among these attempts a remarkable role is played by survey studies which try to measure and explain citizens’ tax morale, understood as an ‘intrinsic motivation’ or ‘interiorized will’ to pay taxes [18, 61]. Such studies seek to explain tax morale by taking declared tolerance towards tax evasion as a proxy, and including it as dependent variable in regression models. Even though the results are often inconclusive, they give interesting information about the statistical correlations between tax morale and different socio-demographical variables (age,
gender, marital status, educational level, or income level), as well as ideological or attitudinal variables (such as religious beliefs, patriotism, or trust in institutions; see a useful overview in Torgler[61]).

All these contributions suggest that the standard economic approach alone is not able to account for a complex social phenomenon such as tax evasion. However, survey data analysis is insufficient to test properly the causal mechanisms involved in such phenomenon, since the description of statistical correlations does not open the ‘black box’ of the generative causal processes that bring about the aggregated outcomes [37]. That is why a remarkable number of studies have recently tried to explain tax evasion by adopting one of the two following methodological strategies: on the one side, experimental designs along the lines of behavioural economics and psychology [4, 5, 41, 56]; on the other, agent-based computational methods.

Although the number of works using agent-based models to explain tax fraud is still small, most of them seek to formalize and test different types of social interaction effects. A brief chronological overview of these studies could be summarized as follows:

- The first attempts to apply agent-based methodology to the study of tax compliance are due to Mittone and Patelli [51], Davis et al. [25], and Bloomquist [15] who is the first in using the software NetLogo (also used in SIMULFIS). This model presents interesting features: agents are programmed with a higher number of properties, the audit probability and its effects are determined in a more complex way, and the results are tested against real data.
- Subsequently we find the model series EC* by Antunes, Balsa et al.[8–11, 13]. The EC* models are made increasingly complex by introducing agents with memory, adaptive capacities, and social imitation. The most remarkable novelties in these models are the inclusion of tax inspectors able to decide autonomously and, above all, the explanation of non-compliance with indirect taxes through collusion between sellers and buyers.
- The NACSM model by Korobow et al. [44] analyses the relationship between tax compliance and social networks, using a Moore neighbourhood structure in which each agent has eight adjacent neighbours in a two-dimensional grid.
- More recently, the proposal by Zaklan et al.[66–68] adapts Ising physical model to the tax field: instead of elementary particles interacting in different ways as a function of temperature, we have individuals behaving in different ways as a function of their level of dependence on their neighbours’ behaviour.
- The TAXSIM model by Szabó et al. [58–60] presents a particularly complex design, since it includes four types of agents (employers, employees, the government, and the tax agency). It also takes into account factors such as agents’ satisfaction with public services, which depends on their previous experience and on that of

\[d\] In Spain, some works following this approach are available [53, 6, 3, 1, 48].

\[e\] Bloomquist [16] summarize and compare the three models mentioned in this paragraph.

\[f\] An overview is available in Antunes et al. [9].
their neighbours.

- Hedström and Ibarra [38] have proposed a social contagion model inspired by the principles of analytical sociology in order to show how tax evasion may spread as a consequence of tax avoidance's social contagiousness.

- Finally, Bloomquist [17] deals with tax compliance in small business by modelling it as an evolutionary coordination game. His model is calibrated with data from behavioural experiments.

In short, social simulation using agent-based models is a promising research option in a field in which, despite the abundant literature, significant and uncontro- versial results have been rare and hardly coordinated. More specifically, there are some key questions which are not still solved by the literature on the matter:

- To what extent is rational choice theory enough to explain estimated levels of tax compliance?
- What is the effect of normative commitments on tax compliance?
- What is the effect of social influence on tax compliance?
- Which social scenario optimizes tax compliance?
- Which combination of tax policies is able to reduce tax evasion?
- How to calibrate empirically an agent-based model for the study of tax compliance?

SIMULFIS aims to provide a computational tool able to shed some light on these questions and other similar ones, by going beyond traditional economic approaches and integrating a diversity of factors and mechanisms which may cause different levels of tax evasion.

3. Description of the Model

3.1. Main features of SIMULFIS

SIMULFIS offers some highlights that distinguish it from other similar models; the design of SIMULFIS makes it capable of more realistic simulations and more detailed empirical calibration than previous models. The most important aspects of this novel design are:

1. A ‘filter’ approach to tax decisions: agents decide how much income they evade after going through four successive filters that affect their decision: opportunity, normative commitments, rational choice, and social influence. This approach aims to capture recent developments in behavioural social science and cognitive decision theory which disfavour the usual option of balancing all determinants of decision in a single individual utility function [14, 30, 33]. Therefore, tax compliance is produced by a combination of mechanisms, most of which may be activated or de-activated in order to run controlled experiments.

2. Since our main focus is behavioural, SIMULFIS outcomes go beyond traditional indicators for compliance (such as the amount of their personal income
agents evade) towards determining how much relative advantage agents take of their opportunities to evade: thus we define agent’s ‘fraud opportunity use rate’ (FOUR) as the main dependent variable of the behavioural experiments that SIMULFIS is able to execute.

(3) Different degrees of opportunity to evade may be assigned to different categories of agents.

(4) Agents’ normative commitments and fairness concerns towards taxation are modelled in a complex way, taking into account factual as well as normative beliefs, and relative deprivation feelings [46, 47].

(5) Agents’ decision algorithm goes beyond binary or ternary choice which is typical in previous models (‘evade/do not evade’, ‘evade more/evade less/do not evade’). In SIMULFIS, agents maximize a utility function to decide what percentage of their income they will conceal.

(6) Finally, SIMULFIS makes it possible to assign different weights to social influence in agents’ decision algorithm.

3.2. Model parameters

3.2.1. Agents’ random properties

A first group of two parameters change their values randomly for each agent in each simulation’s starting point, which is to say in each ‘world’ when it is generated:

(1) Income level. Agents are assigned an amount of annual income following an exponential distribution. In the results showed in section 4, SIMULFIS is calibrated empirically for Spanish income distribution (see Table 1). The top of the distribution has also been adjusted for including a small percentage of big fortunes. After the distribution has been completed, the model assigns each agent to one of three ‘income levels’: ‘high’ (the top decile of the distribution), ‘low’ (the three lowest deciles of the distribution), and ‘middle’ (the six deciles left in between). The distribution may be differentiated for self-employed workers and wage-earners in order to calibrate the model in a more realistic way.

(2) Social network. Agents are randomly linked with a number of neighbours under some constraints: each agent has a minimum of 10 neighbours, and 80% of each agent’s neighbours are similar to her in terms of occupational status and income level. However, it is possible to change the value of these two constraints.

3.2.2. Exogenous parameters (controlled)

(1) Tax rates. The model allows the definition of different income tax rates and brackets, thus offering the possibility of empirical calibration for specific existing tax systems or even counterfactual tax policies.

(2) Occupational status. It is possible to determine the percentage of wage-earners in the population, being the rest self-employed.
Table 1. Income decile distribution for the Spanish population (Euros)

<table>
<thead>
<tr>
<th>Decile</th>
<th>Wage earners</th>
<th>Self-employed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min.</td>
<td>Max.</td>
</tr>
<tr>
<td>1</td>
<td>300</td>
<td>6,828</td>
</tr>
<tr>
<td>2</td>
<td>6,828</td>
<td>9,000</td>
</tr>
<tr>
<td>3</td>
<td>9,000</td>
<td>11,124</td>
</tr>
<tr>
<td>4</td>
<td>11,136</td>
<td>14,720</td>
</tr>
<tr>
<td>5</td>
<td>12,720</td>
<td>14,400</td>
</tr>
<tr>
<td>6</td>
<td>14,400</td>
<td>15,600</td>
</tr>
<tr>
<td>7</td>
<td>15,600</td>
<td>18,000</td>
</tr>
<tr>
<td>8</td>
<td>18,000</td>
<td>21,120</td>
</tr>
<tr>
<td>9</td>
<td>21,180</td>
<td>25,200</td>
</tr>
<tr>
<td>10</td>
<td>25,200</td>
<td>109,116</td>
</tr>
</tbody>
</table>

Note: Source: Household Budget Survey, 2008 (Base 2006). National Statistics Institute - INE.

(3) **Support for progressivity in the tax system.** It is possible to determine the percentage of agents that support the principle of progressivity in the tax system, so that it may be empirically calibrated with data from attitudinal survey studies.

(4) **Income threshold for receiving social benefits.** SIMULFIS allows to establish the income threshold which determines eligibility for a means-tested public cash benefit, so that if an agent’s net income after tax is below the threshold, it is topped up to reach that level. The marginal withdrawal rate of the benefit is 100%, so that each eligible agent only receives the difference between his declared income and the minimum income determined by the threshold.

(5) **Audit rate.** The model allows to give different values to the probability for any agent of being randomly audited.

(6) **Amount of fines.** It is possible to determine the amount of fines as a percentage over the tax evaded. In SIMULFIS present stage there is no chance for tax evaders to be audited but not sanctioned: when a tax evader is randomly audited, then she pays the fine.

(7) **Behavioural filters.** SIMULFIS allows to activate and de-activate two different behavioural filters (see Figure 1): normative commitments (N) and social influence (SI). On the contrary, the other two filters are always activated, since they are necessary for the agents to make a decision: they are opportunities to evade (O) and rational choice (RC).

Fig. 1. Behavioural filters.
(8) Social influence coefficient. The strength of social influence is modelled as a numerical value from 0 to 1, which is to be determined in each simulation.

3.2.3. Endogenous parameters (generated)

Some parameters have values that are endogenously determined by the model: their values at each period of the simulation depend on agents’ decisions in the previous periods. Table 2 displays those parameters and the affected behavioural filter in each case (see below for a detailed description of the role of these parameters).

<table>
<thead>
<tr>
<th>Updates</th>
<th>Affected filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived agent’s audit probability</td>
<td>RC</td>
</tr>
<tr>
<td>Eligibility for benefits</td>
<td>RC &amp; N</td>
</tr>
<tr>
<td>Tax balance (personal and in the neighbourhood)</td>
<td>N</td>
</tr>
<tr>
<td>Perceived progressivity of the tax-benefit system</td>
<td>N</td>
</tr>
<tr>
<td>Neighbourhood’s compliance rate</td>
<td>SI</td>
</tr>
</tbody>
</table>

Note: RC=Rational choice; N=Normative; SI=Social influence.

3.3. Decision algorithm

3.3.1. Decision outcome: FOUR

The main behavioural aim of the SIMULFIS decision algorithm is to compute the ‘fraud opportunity use rate’ (FOUR) of each agent. The basic idea is illustrated in Figure 2 with an example: taxpayers A and B have both a gross income of 100, and they both decide to hide 10 (that is 10% of their gross income); but taxpayer A had the chance to hide 50, while taxpayer B could only hide 20. So, though in absolute terms they comply the same, in relative terms taxpayer B is making use of 50% of his opportunity to evade ($\text{FOUR}_B=50\%$), while taxpayer A only makes use of 20% ($\text{FOUR}_A=20\%$).

This way of modelling agents’ compliance captures the realistic idea that a sizeable part of tax revenue is often simply ensured by income withholding at source, and therefore does not depend on agents’ decisions at all. We think that the complication introduced in the model by computing FOUR is theoretically justified because this is a much better indicator of the intensity of agents’ tax fraud efforts than the amount of money evaded or the percentage of their income they evade. As shown by our example in Figure 2, similar percentages of income evaded may reflect very different evasion efforts, and the reverse is also true.
3.3.2. Opportunity filter (O)

The first behavioural filter is defined as the percentage of an agent’s income she has objective chance to conceal. In order to determine some reference values for different agents’ opportunities, we adopt some simple (and arguably realistic) assumptions:

1. Wage-earners have fewer opportunities to evade than self-employed workers, because their income is typically withheld at origin in a more substantial proportion.
2. Agents with high income (the top decile of income distribution) have more opportunities to evade than the rest, because they receive income from many different sources or they have the resources, techniques, and abilities needed to successfully conceal a higher proportion of it.
3. For similar reasons, agents with middle income have more opportunities to evade than agents with low income (the lower three deciles of income distribution).
4. For all agents there is some percentage of their income they cannot conceal, since the government always has some information on at least a minimum proportion of every agent’s income.

Following these assumptions, Table 3 shows the reference values adopted so far in SIMULFIS for each category of agents in terms of income level and occupational status.

Table 3. Reference values for opportunities to evade (in % of agents’ gross income)

<table>
<thead>
<tr>
<th>Income Level</th>
<th>Self-employed</th>
<th>Wage-earners</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>80</td>
<td>30</td>
</tr>
<tr>
<td>Medium</td>
<td>60</td>
<td>20</td>
</tr>
<tr>
<td>Low</td>
<td>60</td>
<td>10</td>
</tr>
</tbody>
</table>
3.3.3. Normative filter (N)

The second behavioural filter aims to model agents’ normative attitudes and satisfaction feelings towards the tax system’s design and performance in terms of its fairness. The filter combines two elements in order to determine the level of satisfaction of each agent: (1) agents’ satisfaction with the progressivity of the tax system, and (2) agents’ satisfaction with their tax balance when compared with that of their neighbourhood:

(1) **Satisfaction with the progressivity of the tax system.** It is a function of:

(a) Agents’ support for the progressivity principle in the tax system (their normative beliefs on progressivity). This is an exogenous parameter, so the percentage of agents supporting progressivity is controlled. Agents are randomly assigned normative beliefs about progressivity according to that aggregated percentage.

(b) Agents’ perception of ‘real’ progressivity in the tax system (their factual beliefs on progressivity): it is updated after each tax period. The system is perceived as progressive if the income ratio, after taxes and benefits, between the richest 10% and the poorest 10% is reduced by more than 30%.

(c) If agents support progressivity and perceive that the system is progressive, they are ‘satisfied’; otherwise, they are not.

(2) **Satisfaction with the tax balance.** Agents’ satisfaction with their tax balance is determined by comparing their personal tax balance with that of their neighbourhood. This method tries to capture the well-known findings of the literature on relative deprivation, which show that people’s feelings of satisfaction with their endowments depend more on the comparison with their reference group than on the amount enjoyed in absolute terms [47].

(a) Agents’ personal tax balance is computed by comparing their personal tax burden \(X_{it}\) with the benefits they eventually receive \(Z_i\): agent \(i\) is a ‘net contributor’ if \(X_{it} > Z_i\), or a ‘net recipient’ if \(X_{it} \leq Z_i\). (See Table 4 below for the notation).

(b) To compute their neighbourhood’s tax balance, agents observe whether the majority (more than 50%) of agents in their neighbourhood (including themselves) are net contributors or net recipients.

(c) If an agent is a net contributor while the majority of her neighbours are net recipients she is ‘unsatisfied’; otherwise, she is satisfied.

Once the two components of agents’ satisfaction are determined, the effect of the normative filter (N) on compliance is modelled as a reduction of agent’s concealable income resulting from their opportunity filter (O), so that:

(1) If an agent is satisfied in both senses 1 (progressivity) AND 2 (tax balance), she reduces in two thirds (66%) the proportion of income she may conceal.
(2) If an agent is satisfied only in sense 1 OR in sense 2, the reduction is in one third (33%).
(3) If an agent is NOT satisfied in any sense, she may conceal the full percentage of income resulting from the opportunity filter (O).

3.3.4. Rational choice filter (RC)

Over the percentage of their gross income resulting from filters O and N (the income agents may conceal), agents rationally maximize their net income by calculating the expected utility of a set of eleven outcomes. Agents maximize their expected utility according to the following equation, which is an adaptation for the SIMULFIS model of the classical tax fraud expected utility function by Allingham and Sandmo [2]:

\[
UE_i(X_i) = (1-p_i) \sqrt{(Y_i - X_i t_{X_i} + Z_{X_i}^X + Z_{X_i}^Y)} + p_i \sqrt{(Y_i - X_i t_{Y_i} - \theta(Y_i t_{Y_i} - X_i t_{X_i}) + Z_{Y_i}^Y)}
\]  

Where (see notational guide in Table 4)

\[Z_{X_i}^X = M - X_i (1 - t_{X_i}); \quad Z_{Y_i}^Y = M - Y_i (1 - t_{Y_i}); \quad Z_{X_i}^X, Z_{Y_i}^Y \geq 0 \]  

According to this function, an agent’s decision to declare income \(X_i\) is a function of tax rates \(t\), fine \(\theta\), her real income level \(Y_i\), and the probability \(p\) of being caught if she evades. We assume homogeneous risk aversion by using cubic roots in both addends of the equation. We also include the expected social benefit, which agents compute by determining their eligibility in the immediately preceding period of the simulation. Note that when \(X_i (1 - t_{X}) < M\) but \(Y_i (1 - t_{Y}) \geq M\), that is, when the agent is not legally eligible for benefits but she evades enough to be so, then \(Z_{Y_i}^Y = 0\). Similarly, when \(X_i (1 - t_{X}) \geq M\), that is, when the agent is not eligible whether she evades or not, then \(Z_{X_i}^X = 0\) and \(Z_{Y_i}^Y = 0\).

Agents’ perceived probability of being sanctioned if they evade \(p\) is randomly distributed in the first period of the simulation and afterwards is updated endogenously as a function of the agent’s audit record in all previous periods and the audit rate in the agent’s neighbourhood in the immediately previous period, according to the following equation:

\[p_i = \left(\frac{I_i}{R} - \frac{I_{iv}}{V_i}\right) / 2\]  

\(^a\)SIMULFIS uses a discrete computational approach to determine a sequence of eleven expected outcomes in terms of agents’ net income, which results from reducing concealed income by intervals of 10% from evading 100% to 0% of agents’ concealable income. Since the expected utility formula we are using introduces substantive complications in relation to the classical one by Allingham and Sandmo (such as a progressive tax rate and a social benefit), this way of formalizing expected utility makes the computational working of the model easier, while ensuring the consistency of agents’ decisions.

\(^b\)We do not use square root to avoid applying it to eventual negative numbers in the second addend (which could be the case, for example, if an agent declares a low percentage of her income and fines are very hard).
It should be noted that, despite different filters and mechanisms affecting agents’ final decision on compliance, rational choice has always some weight in the final decision (except under full social influence: see footnote j). We take this as a realistic assumption, since an economic decision like tax compliance is almost always rationally considered by taxpayers, and, in most cases, assessed by experts or professionals.

3.3.5. Social influence filter (SI)

The last behavioural filter models the extent to which agents’ FOUR converge to that of their neighbourhood as a result of any kind of social influence. [21, 22, 27, 28, 54, 55, 65] In SIMULFIS, the strength of social influence is determined by an exogenous parameter ($\omega$) equal for all agents, ranging (0,1) from no social influence.

The operation of social influence mechanisms affecting tax evasion behaviour has been recently questioned by some scholars [38] on the basis of the ‘privacy objection’: since tax compliance is taken to be private and unobservable by peers, no social influence could take place. However, as survey studies repeatedly show [40, 23], citizens usually have an approximate idea on the tax compliance level in their country, occupational category, or economic sector, its evolution in time, and its main causes; these ideas may be formed from information received through mass media, personal interaction, or indirect inference (for example, shared social characteristics, when compared with economic lifestyles, may be proxies for inferences about neighbours’ and peers’ tax compliance). Additionally, in countries where there is low tax morale and high social tolerance towards tax evasion (such as Spain), it is usual to have access to public ‘street knowledge’ about personal tax compliance, and to give and receive advice between neighbours and peers on how to evade. Finally, there is some literature modelling social influence mechanisms triggered by estimated or revealed information on criminal and dishonest behaviour [26, 34, 35].
to full social influence. After applying the RC filter, agents’ FOUR ($\alpha_i$) converge to the median FOUR in their neighbourhood ($\alpha_v$), according to $\alpha_i + \omega(\alpha_v - \alpha_i)$. The result of this calculation is the agent’s final FOUR, which is expressible in terms of the percentage of the agent’s income which is declared or evaded, and in terms of absolute amount of income evaded.  

3.3.6. An example of the decision algorithm

Figure 3 displays a numerical example of how agents’ decision algorithm operates. The numbers at the upper level express percentages of an hypothetical agent’s income, and how they change when the agent goes through the consecutive behavioural filters; as explained above, the opportunity and normative filters result in a maximum percentage of concealeable income, while the rational choice and the social influence filters lead the agent to a decision as to what percentage of her income she will evade.

The numbers at the lower level express the equivalents to these two latter percentages in terms of FOUR; once the agent has gone through the rational choice filter, the resulting percentage is transformed in terms of FOUR (vertical descending arrow); this FOUR is compared with the agent’s neighbourhood’s FOUR (bidirectional vertical arrow); then, the application of the social influence formula (see section 3.3.5 above) results in a different FOUR (diagonal arrow), which is again transformed into a percentage of income to be evaded by the agent (vertical ascending arrow). Specifically, the example works as follows:

(1) Let us assume that in a given period of a simulation, agent $i$ after the O filter may conceal 60% of her income.

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Note that, when $\omega = 1$ (full social influence), the individual effect of the RC filter is cancelled; and when $\omega = 0$ (no social influence), the agent keeps his original FOUR resulting from the RC filter.
(2) The maximum she can evade after applying the N filter is 40% of her income (for example, because she is satisfied only with respect to her tax balance but not with respect to the progressivity of the system, so she reduces in one third her opportunity to evade).

(3) Let us assume then that after applying the RC filter, this percentage is further reduced to 20% of her income. Therefore, her FOUR ($\alpha_i$) will be 33.3% (resulting from $20/60$).

(4) Let us also assume that in the previous period her neighbourhood’s median FOUR ($\alpha_v$) was 10%. If the social influence coefficient ($\omega$) is set to 0.5, the agent’s FOUR after the SI filter will be: $\alpha_i + \omega(\alpha_v - \alpha_i) = 21.7\%$.

(5) The resulting FOUR of 21.7% is equivalent to conceal 13% of the agent’s income, since she is making use of 21.7% of her initial opportunities, which were 60%, so: $21.7\% \times 60\% = 13\%$. So in this example the SI filter affects the agent’s compliance by reducing the percentage of income she decides to evade from 20% to 13%.

3.4. Model dynamics

The operation of the model is as follows: when the SIMULFIS is initialised, agents randomly receive a salary and a number of neighbours in the way described above. Then they go through the decision algorithm, and end up making a decision about how much of their income they declare, as a result of the activated behavioural filters. Their salaries are taxed and random audits and fines are executed. Then benefits are paid to those who are eligible, and endogenous parameters are updated for the next period (see Figure 4).

Fig. 4. Model dynamics.
3.5. Outcomes

The main outcome of SIMULFIS’ simulations is a set of decisions by each agent on how much income she evades at each period of a simulation, expressed in terms of agents’ FOUR:

1. Mean FOUR of each agent in all periods of a simulation (typically 100).
2. Mean FOUR of all agents (typically 1,000) in each period of a simulation.

When agents’ FOUR is converted into the equivalent amounts of evaded income in euros, we may have also outcomes such as:

1. Mean percentage of gross income concealed by each agent in all periods of a simulation.
2. Mean percentage of gross income concealed by all agents in each period of a simulation.
3. For each agent, the absolute amount of tax evaded, which is the result of $Y_i t_Y - X_i t_X$.

From individual outcomes it is possible to compute aggregated outcomes for the system, such as:

1. Aggregated concealed income as a percentage of total income in the system.
2. Aggregated fiscal pressure as a percentage of total income in the system.
3. Aggregated absolute amount of tax evaded, which is the result of:

$$\sum_{k=1}^{N} (Y_i t_Y - X_i t_X)$$

4. Aggregated tax gap: aggregated tax evaded as a percentage of total tax due, which is the result of:

$$\sum_{k=1}^{N} \left[ \left( \frac{Y_i t_Y - X_i t_X}{Y_i t_Y} \right) 100 \right] / N$$

Finally, all these results may be differentiated by different initial settings, categories of agents, values of a parameter, and so on, thus allowing SIMULFIS users to run controlled virtual experiments on tax compliance behaviour.

4. Some Experimental Results

4.1. Experimental design: description of the simulations

We run a set of simulations in order to test SIMULFIS internal validity: that is, whether the model works as theoretically expected and is reliable. The experimental

\(^k\)Note that progressive tax rates applied to different income brackets are not necessarily the same for total gross income than for declared income, so this calculation is necessary.
design presented here aims to test specifically the different effect on tax compliance of different combinations of behavioural filters, under different scenarios of deterrence in terms of audits and fines. As a bridge to a more refined empirical or external validation of the model in a second stage of the project, we also analyse some economic results of the simulations when it is calibrated for the Spanish case. However, it should be noted that a complete empirical validation of the model is strongly dependent on the availability of reliable data on tax compliance and tax behaviour in concrete empirical cases. Besides, although the number of parameters of the model is high, we have only manipulated three of them (behavioural filters, audits, and fines), in order to achieve an acceptable equilibrium between fundamental work on social mechanisms and the attempt to fit the Spanish scenario.

The experimental design can be summarized as follows: we run 1,920 simulations with 1,000 agents and 100 tax periods for each simulation. We test four behavioural experimental conditions (EC), which activate different combinations of behavioural filters (recall that the opportunity filter O is always activated): in EC1 agents decide only on the basis of rational choice (RC filter); in EC2, RC and the normative filter (N) are both active; in EC3, RC is supplemented with the social influence filter (SI); finally, in EC4, all filters are active (RC + N + SI). We also study 16 different deterrence scenarios: audit rates of 15%, 30%, 45%, and 60%, with fines of 1.5, 3, 4.5, and 6 as multipliers of the amount of evaded tax. Three social influence scenarios are considered, with $\omega = 0.25, 0.50, 0.75$. Each simulation is run in ten different ‘worlds’ (different random initial assignations of neighbours and income).

Some of the exogenous parameters of the model are calibrated empirically for the Spanish case, as detailed in table 5.

4.2. Behavioural outcomes

A first set of experimental results have to do with the behavioural outcomes of the simulations, taking agents’ FOUR as the main indicator of tax compliance. In all simulations, a robust equilibrium seems to be reached after few periods, and the system stabilizes around a certain average level of compliance in terms of agents’ mean FOUR (see, for example, figure 6). Figures 5 and 6 show the main trends of tax compliance under different behavioural conditions and deterrence scenarios, with $\omega = 0.5$. All plots of this type show the mean FOUR of the 10 simulations executed (10 different worlds) for the entire population of agents in each round.

In Figure 5, the plot on the left shows the (arguably) most realistic conditions in terms of deterrence. In this case, it appears that only EC2 (RC+N, red line) and EC4 (RC+N+SI, purple line) predict plausible levels of tax compliance, and the latter seems to be the optimal condition. This suggests, in line with recent literature, that rational choice alone is not enough to explain realistic levels of tax compliance.

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1The number of simulations executed (1,920) is the result of multiplying four experimental conditions by sixteen deterrence scenarios, by three social influence scenarios, by ten different ‘worlds’.
Table 5. Reference value for some exogenous parameters in SIMULFIS’ experimental design

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Reference value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tax rate a</td>
<td>Less than 5,050€ (0%)</td>
</tr>
<tr>
<td></td>
<td>5,051 to 17,360€ (24%)</td>
</tr>
<tr>
<td></td>
<td>17,361 to 32,360€ (37%)</td>
</tr>
<tr>
<td></td>
<td>32,361 to 120,000€ (43%)</td>
</tr>
<tr>
<td></td>
<td>120,001 to 175,000€ (44%)</td>
</tr>
<tr>
<td></td>
<td>More than 175,000€ (45%)</td>
</tr>
<tr>
<td>Occupational status distribution b</td>
<td>18.1% self-employed</td>
</tr>
<tr>
<td></td>
<td>81.9% wage earners</td>
</tr>
<tr>
<td>Support for progressivity in the tax system c</td>
<td>80.0%</td>
</tr>
<tr>
<td>Income threshold for receiving social benefits d</td>
<td>8,700€</td>
</tr>
</tbody>
</table>

Note:

a Calibrated for Spanish income tax rates and brackets (2011).


c Calibrated for Catalonia 2010[52].

d 50% of median income (poverty threshold).

However, an interesting fact is that as deterrence is made harder (see the right plot), EC4 (RC+N+SI) becomes suboptimal in front of EC2 (RC+N) and even in front of EC1 (RC, blue line).

![Fig. 5. Mean FOUR by deterrence conditions (2 extreme scenarios). RC=Only Rational Choice filter activated. RC+N=Rational Choice and Normative filters activated. RC+SI=Rational Choice and Social Influence filters activated. RC+N+SI=Rational Choice, Normative, and Social Influence filters activated. Audits in % and fines as multipliers of evaded tax. Y axis represents FOUR; X axis represents time.](image-url)
Figure 6 shows this trend in an extended way across all deterrence scenarios. It is clear that harder deterrence always improves compliance (generating a lower mean FOUR), but at the same time operates a substantial change in the ‘optimality ordering’ of the four behavioural experimental conditions, with only one exception: EC2 (RC+N) always fares better than EC1 (RC alone). This is not surprising, since the N filter was modelled so that it can only improve agents’ compliance. What is unexpected, and contrary to usual theoretical expectations in the literature, is that social influence may have an ambivalent relative effect depending on deterrence levels. We will return to this later.

In order to isolate the relative effect of audits and fines on agents’ compliance, we compute the aggregated mean FOUR for all simulations with similar values for audits and for fines (Figures 7 and 8). Again it is clear, and theoretically to be expected, that higher audits and fines always improve compliance, but increasing audits is proportionally more effective than rising fines. This outcome is in line with the elasticity estimates from Alm and Jacobson [4] and SIMULFIS does not include tax inspectors as strategic agents in the model, our result is independent from the well-known claim by Tsebelis [63, 64] that...
with results obtained in most laboratory experiments [4, 31].

![Graph showing mean FOUR by deterrence condition (audits).](image1)

**Fig. 7.** Mean FOUR by deterrence condition (audits). RC=Only Rational Choice filter activated. RC+N=Rational Choice and Normative filters activated. RC+SI=Rational Choice and Social Influence filters activated. RC+N+SI=Rational Choice, Normative, and Social Influence filters activated. Audits in % and fines as multipliers of evaded tax. Y axis represents FOUR; X axis represents time.

![Graph showing mean FOUR by deterrence condition (fines).](image2)

**Fig. 8.** Mean FOUR by deterrence condition (fines). RC=Only Rational Choice filter activated. RC+N=Rational Choice and Normative filters activated. RC+SI=Rational Choice and Social Influence filters activated. RC+N+SI=Rational Choice, Normative, and Social Influence filters activated. Audits in % and fines as multipliers of evaded tax. Y axis represents FOUR; X axis represents time.

Figure 9 display the relative differences between mean FOUR in each experimental condition using EC1 (RC alone) as a baseline. This is a measure of how much deviation from the strict rational choice scenario is operated in terms of compliance by the rest of behavioural filters. It is confirmed again that N always pulls up compliance, but SI has an ambivalent effect depending on deterrence levels. However, in the majority of scenarios where a behavioural filter is added to rational choice, there is a decrease in FOUR (and thus compliance increases); additionally, in most higher penalties have no effect on crime.
cases, this decrease is proportionally more intense than the increase operated by the addition of the SI filter in some scenarios with very hard deterrence.

To see this more clearly, Figure 10 isolates the net effect of SI on compliance, in comparison with the conditions where no social influence is present. It is clear that the effect of SI on FOUR is positive and marginally decreasing as deterrence is harder, and ends up (at the right side) by being increasingly negative (and so, by improving compliance under medium and low deterrence levels).

Figure 11 and Figure 12 confirm that all the trends mentioned so far, and specially the ambivalent effect of social influence, are not substantially affected by different values of $\omega$ (the social influence coefficient), although these values intensify the tendency correspondingly: a lower value of $\omega$ makes SI scenarios become suboptimal more slowly as deterrence is harder, while a higher value speeds the pattern up.

Why is this effect taking place? The reason is that social influence makes tax compliance less sensitive to increased deterrence levels: since decisions are interdependent and not only based on individual cost-benefit calculations or normative attitudes, individual decisions on compliance are ‘adjusted’ upwards or downwards depending on the neighbourhood; both trends may partially cancel each other on the global mean, making the difference we are observing. When deterrence is hard enough, scenarios where this ‘adjustment’ does not take place will logically fare better in terms of compliance. This effect is somehow capturing a well-known social
Fig. 10. FOUR differences (baseline: conditions without Social Influence). In each bar, the vertical label contains the percentage of audits and the fine multiplier; the Y axis expresses FOUR differences with the baseline.

Fig. 11. Mean FOUR by deterrence conditions with $\omega = 0.25$. RC=Only Rational Choice filter activated. RC+N=Rational Choice and Normative filters activated. RC+SI=Rational Choice and Social Influence filters activated. RC+N+SI=Rational Choice, Normative, and Social Influence filters activated. Audits in % and fines as multipliers of evaded tax. Y axis represents FOUR; X axis represents time.
phenomena, but one not much studied in the literature on tax compliance: agents who take into account their peers’ decisions when making their own are less likely to change their behaviour (or are likely to change it with less intensity) as an effect of external or hierarchical pressures from above (such as audits and fines).

4.3. Economic outcomes

A second set of results have to do with how much income in absolute terms do agents evade. At this stage these results have to be interpreted as a test for the plausibility and internal validity of SIMULFIS, and have not necessarily an empirical extrapolation. The outcomes presented in this section, therefore, can be understood as a bridge from theoretical-internal validation (theory-driven simulation) to the potential empirical validation of SIMULFIS (data-driven simulation). In this section the dependent variable and main indicator of aggregated tax evasion is the mean concealed or underreported income, expressed in euros.

Figures 13 to 16 show the mean concealed income by income level and occupational status, for the four behavioural conditions and under different deterrence scenarios.\(^n\)

\(^n\)For the sake of simplicity, only four deterrence scenarios are shown, which correspond to those in the diagonal of Figure 6. In all cases, \(\omega = 0.5\).
Fig. 13. Mean concealed income (€) by income level and occupational status in different deterrence scenarios [Experimental condition: RC (1); audits in % and fines in multipliers of evaded income].

Fig. 14. Mean concealed income (€) by income level and occupational status in different deterrence scenarios [Experimental condition: RC+N (2); audits in % and fines in multipliers of evaded income].
Fig. 15. Mean concealed income (€) by income level and occupational status in different deterrence scenarios [Experimental condition: RC+SI (3); audits in % and fines in multipliers of evaded income].

Fig. 16. Mean concealed income (€) by income level and occupational status in different deterrence scenarios [Experimental condition: RC+N+SI (4); audits in % and fines in multipliers of evaded income].
As theoretically expected, the general trend is that self-employed workers evade much more as an average than wage-earners, and that agents with high income evade much more than agents with middle and low income. However, in Figure 13 (EC1: RC alone) we see that as deterrence is made harder, high-income agents start to evade less as an average than those with middle and low income; this is the logical effect, for rational agents, of decreasing marginal tax rates, but also of the fact that the amount of fines in these scenarios is more costly for high-income evaders. Interestingly, social influence (Figures 15 and 16) shows again an ambivalent effect, by boosting mean underreported income by self-employed high-income workers under hard deterrence levels, in comparison with the conditions where no social influence is present (Figures 13 and 14).

Figures 17 to 20 show the aggregated volume of underreported income under the same conditions than Figures 13-16. Another interesting result appears: though, as we saw in Figures 13 to 16, high-income agents evade a higher mean income than the rest, the largest portion of concealed income in aggregated terms is to be found, in most scenarios, among middle-income wage earners, mainly because of their number. Similarly, and for the same reason, wage earners seem to concentrate a higher volume of concealed income than self-employed agents, but the latter’s portion of underreported income is still high when related to their small number. The relative effect of social influence is again to raise the volume of concealed income for high-income self-employed workers.

Fig. 17. Volume of concealed income (€) by income level and occupational status in different deterrence scenarios [Experimental condition: RC (1); audits in % and fines in multipliers of evaded income].
Fig. 18. Volume of concealed income (€) by income level and occupational status in different deterrence scenarios [Experimental condition: RC+N (2); audits in % and fines in multipliers of evaded income].

Fig. 19. Volume of concealed income (€) by income level and occupational status in different deterrence scenarios [Experimental condition: RC+SI (3); audits in % and fines in multipliers of evaded income].
Figure 20. Volume of concealed income (€) by income level and occupational status in different deterrence scenarios [Experimental condition: RC+N+SI (4); audits in % and fines in multipliers of evaded income].

Figure 21 gives another measure of aggregated tax evasion: the total volume of underreported income as a ratio of the total income in the system, by behavioural and deterrence conditions. An interesting point to note here is that if we rely on the abovementioned estimations of a volume of tax fraud around 20% of the Spanish GNP, then the closest scenarios to this value are EC1 (RC alone) under medium level of deterrence (which is unrealistic) and EC3 (RC+SI) under low levels of deterrence (which correspond better to Spanish real tax audits and fines). This seems to suggest that the SI filter may introduce more realism in the model than the N filter, and that EC2 and EC4 underestimate the level of tax fraud, while EC1 overestimates it.

An example of a more fine empirical comparison may be the one displayed in Table 6, which shows the relative differences between self-employed workers’ and wage earners’ mean underreported income according to an empirical estimation and as predicted by SIMULFIS. Since the values are broadly similar for a close time period, we dare to claim that SIMULFIS is in the right track for achieving good empirical fit in future stages of the project.

5. Conclusions and future research

This article has offered a detailed description of SIMULFIS, a computational behavioural model for the simulation of tax evasion and tax compliance. We have presented the results of a first experimental design implemented to test the theoretical and internal validity of SIMULFIS, and specifically the different effect on tax

Table 6. Mean declared and underreported income gap between self-employed workers and wage earners: SIMULFIS results and estimations for Spain.

<table>
<thead>
<tr>
<th>Gap between self-employed and wage earners</th>
<th>SIMULFIS</th>
<th>Spain</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean declared income (€)</td>
<td>- 5,337 €</td>
<td>- 4,875 €</td>
<td>GESTHA, 2009[32]</td>
</tr>
<tr>
<td>Mean concealed income (%)</td>
<td>25.5%</td>
<td>25-30%</td>
<td>Martínez, 2011[49]</td>
</tr>
</tbody>
</table>

compliance of different combinations of behavioural filters, under different conditions of deterrence in terms of audits and fines. The results also include the analysis of some economic outcomes which may be understood as a bridge to a more refined empirical or external validation of the model in a second stage of the project. As it was noted, a complete empirical validation of the model is strongly dependent on the availability of reliable data on tax compliance and tax behaviour in empirical cases.

The main conclusions to be drawn from the analysis of these results could be summarized as follows:

(1) As suggested by theoretical literature on tax compliance, strict rational agents would produce much less compliance than it is usually estimated, except with unrealistically high deterrence levels. This strongly suggests that rational choice
theory is not enough on its own to generate empirically estimated compliance levels through simulations and that other normative and social mechanisms are therefore necessary in any plausible model of tax compliance behaviour.

(2) Contrary to what is assumed by other agent-based models of tax evasion, social influence does not always optimize compliance. In particular, it has been shown that when deterrence is strong, RC (rational choice) and RC + N (rational choice plus normative commitments) fare better in terms of compliance. The reason of this ambivalent effect of social influence is that its presence, by making agents decisions dependent on those of their peers, makes tax compliance level less sensitive to increased deterrence levels. So contrary to what Korobow et al. seem to assume [44], social influence need not have the same directional effect on compliance independently of deterrence level. This social influence effect, as well as its foundations at the micro level, would be difficult to observe and analyze without the aid of an agent-based model such as SIMULFIS.

(3) Similarly to most experimental studies [4, 31], we find that audits are comparatively more effective than fines in order to improve tax compliance. A key factor to explain this may be the link between being audited and being fined. Further experiments performed with SIMULFIS may try to disentangle both facts in order to test whether this trend is confirmed, but the implication so far seems clear that policies to tackle tax evasion should rely more on improving the efficacy of audits, as well as their number and scope, than on raising penalties.

SIMULFIS is an agent-based model which offers many possibilities that further stages of the project will try to develop. To mention only a few, by using SIMULFIS it is possible to design controlled experiments to test the effect of the introduction of unconditional compliers and non compliers in the population, the micro-dynamics of the decision algorithm at the individual agent’s level, the effect of different types of social networks, or the effect of different tax rates and tax policies. SIMULFIS is therefore a flexible tool designed to improve social-scientific research on tax behaviour, a field that, in Kirchler’s words, is “still in its infancy” [41](xv).

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