Abstract - In this paper, we use a computational modeling approach to examine the long-standing social issue of tax compliance. Specifically, we design an agent-based model—the Networked Agent-Based Compliance Model (NACSM)—where taxpayers not only exist within localized social networks, but also possess heterogeneous characteristics such as perceptions about the likelihood of audit and apprehension. When making compliance decisions, agents in our model factor in their neighbors' compliance strategy payoffs. We find that for a given enforcement regime, a world with limited knowledge of neighbor payoffs appears to lead to higher levels of aggregate compliance than when agents are aware of neighbor strategy payoffs and factor these into their individual compliance decisions. As this paper demonstrates the strength and initial results of our approach, we point to the need for further research using the NACSM approach and similar models as well as the development of higher fidelity agent-based compliance models.

BACKGROUND

Tax evasion as a social phenomenon has received increasing amounts of attention in the literature as researchers seek improved approaches to modeling noncompliance. In related research, others have sought approaches that more explicitly account for social phenomena in explaining crime. For example, Glaeser, Sacerdote, and Scheinkman (1996) model the wide variance of crime rates across different geographic areas, taking into account social interactions. Their results indicate that crime (e.g., larceny, burglary, and auto theft) has a significant degree of social interaction that helps explain its variability across different cities, towns and precincts. If in fact most crime does have an element of social interaction as its cause, then it would not be unreasonable to conclude that, since tax evasion is a crime, evasion has social drivers as well. In fact, researchers have tried to incorporate social drivers (e.g., social norms) in explaining noncompliance as conventional economic models over-predict the amount of noncompliant behavior one should observe (Alm, McClelland, and Schulze, 1992). To date, little research has explicitly modeled the role that social networks might play in noncompliant behavior. Though tax authorities tacitly recognize that the sharing of information regarding tax schemes, for example, can promulgate evasive behavior, research and
information on understanding the impact of networks has been limited. Part of the explanation for limited understanding of network impacts on compliance may be because of the high degree of complexity involved in modeling taxpayers as part of a linked network of agents.

In this paper, we take advantage of an agent-based computational modeling approach by designing an agent model—the Networked Agent-Based Compliance Model (NACSM)—where taxpayers not only possess heterogeneous characteristics, but also exist within their own respective social networks. In addition, we build on elements of the existing compliance literature by incorporating the traditional aspects of compliance drivers (penalties, audits, and tax rates) as well. After giving a brief overview of agent-based modeling in the first section, we review in the second section the relevant compliance literature as well as research that has applied the computational social science approach to compliance. Then we discuss some of the basics of computational social science and how it relates to compliance. In the third section, we describe our model, and we discuss results in the fourth section. In the fifth section, we discuss some conclusions and point to areas where our research might be extended.

INTRODUCTION

The most pervasive (and well-employed) model of tax compliance, due to Allingham and Sandmo (1972) (hereafter referred to as “A&S”), describes taxpayer expected utility as a function of tax rates, potential penalties, and probability of audit. Essentially, this approach builds on Becker’s (1968) rational economic agent approach to crime as a lottery. While this model has been used and modified over the decades to address tax compliance, researchers have long struggled with its major shortcoming—it fails to accurately predict at a macroscopic level the very phenomena it seeks to model. More specifically, the A&S model predicts much lower levels of compliance than actually observed in most industrialized nations. With true audit rates averaging at one percent (or less in some periods) in the past few decades, the real puzzle of compliance, as Alm (1991) notes, is why people pay taxes at all.

That the classic expected utility model of tax compliance yields poor predictions of macro compliance levels is not to say that taxpayers do not consider sanctions and penalties for evading, but rather points to other forces at play in individuals’ compliance decisions. Since the advent of this model, however, researchers have widened their lens in looking at the causes of noncompliance. Specifically, the literature has focused on social drivers of compliance such as social norms, individual ethics, and how taxpayers reference themselves to others in their social network. Wenzel (2005) notes that social factors such as “ethics and norms” might not only create deterrents to compliance, but might also mitigate the impact of potential penalties associated with noncompliance. Myles and Naylor (1996) combine the standard model of tax evasion with the idea of social conformity to construct a framework where individuals gain some utility from paying taxes honestly while also enjoying a payoff from conforming to the established social pattern of behavior.

More current research has sought to modify the A&S model to incorporate social factors. For example, Traxler (2006) modifies the classic approach to include “tax morale” and interprets this modification as an “internalized social norm” for tax compliance. His results yield higher levels of compliance given low audit rates. More recently, and in a somewhat different approach to the compliance issue, Feld and Frey (2007) argue that tax compliance
is the result of a “psychological tax contract” where emotional ties and loyalties bond the taxpayer and state together to create a tax morale that reinforces compliance.

**The Agent–Based Approach to Social Science**

Agent–based computational social science involves analyzing social phenomena from the bottom up—i.e., modeling the individual agents of a system. The agent–based approach represents a rapidly evolving and powerful approach to analyzing complex systems. One of the most important characteristics and advantages of agent–based models (ABM), as compared to traditional comparative static models, for example, is the notion of emergent behavior—global, macroscopic patterns of behavior that originate from individual, microscopic agents following a set of rules and interacting with one another.

As noted by Axtell (2000) there are several distinct advantages of the ABM approach as compared to traditional mathematical modeling. First, agent rationality in such models can be modified to allow for less than completely rational agents. Second, though agents may follow the same methodological rule–set (as they do in our NACSM model) it is uncomplicated to endow agents with heterogeneous tastes and preferences, thus deviating from the standard “one agent represents all” approach common in the economics literature. Third, as agent based models are dynamical in nature, there is a record of each agent’s behavior or actions from each period. Thus, agent models create a rich set of synthetic agent data that are the microscopic representatives of the emergent aggregate social structure. Lastly, and importantly for this paper, social networks matter in agent models. Interaction is a key strength of the agent–based approach, as agents can learn and mimic behaviors of other agents. Thus, ABM provides a flexible, natural description of a system that can capture emergent phenomena (Bonabeau, 2002).

Like traditional microsimulation approaches, the ABM approach can also yield insight into the impacts of policy changes on different segments of the population including distributional impacts (e.g., which population segment is most affected by a particular policy change). However, what makes the ABM approach different is that each agent assesses his situation or environment and then subsequently makes decisions according to some individual rule–set. These sets can be distributed across the agents in ways that allow for representation of a heterogeneous population, and can make explicit the results of interactions among the differing agent types. Non–linear, even chaotic, relationships can be observed and evaluated. This is unlike traditional microsimulation, for example, in which microdata do not decide anything—they are simply sifted through a maze of rigid business rules based upon statistical characteristics (e.g., taxable income, gender, head–of–household, etc.). Furthermore, with ABM, agents if so designed can evolve and exhibit unanticipated behaviors and patterns. Moreover, agent models can converge to a stable equilibrium, but as mentioned earlier, can have a great degree of variance in local agent behavior. For example, different agents may journey the gamut of compliance outcomes, with some under-reporting income in some periods and reporting all income in other periods. Yet at the macroscopic view, we are in an overall compliant equilibrium setting. In other words, agent models can be characterized by high degrees of local disequilibria, but exhibit a stable macro–level equilibrium.
OVERVIEW OF ABM COMPLIANCE LITERATURE

Though a comprehensive review of the compliance literature is beyond the scope of this paper, it is necessary to briefly review the body of research in compliance that uses computational agent–based models. There are several papers that have used multiagent–based simulation (MABS) models to examine the tax compliance issue (Bloomquist, 2006). Each of these models attempts to overcome the conventional A&S type approach to modeling compliance.

Bloomquist (2004) developed the tax compliance simulator (TCS)—an agent–based model designed to analyze taxpayer behavior under different enforcement regimes. The TCS can simulate agent responses to changes in audits and penalties, while also examining agent compliance behavior given the opportunities to evade afforded by “less visible” income. Relevant for our paper, Bloomquist incorporates social networks and finds that as the size of an agent’s social network increases, the voluntary compliance rate in the population increases as well, thus pointing to the indirect deterrent effects of audits.

Mittone and Patelli (2000) constructed an agent–based simulation model by building on the research of Myles and Naylor (1996). Mittone and Patelli define three types of taxpayers: honest, imitative, and perfect free–rider. Honest taxpayers derive some of their utility through conforming to the social norm of compliance. Imitative taxpayers receive extra utility by paying an amount that is close to the prevailing mean amount paid in the population. And free–riding taxpayers derive utility from paying low amounts of tax while consuming their respective portions of the public good. Their agent model yields the result that with little enforcement, and even with some amount of honest taxpayers, the agent society converges to “almost total evasion.”

Davis, Hecht, and Perkins (2003) develop a computational agent model where agents possess limited knowledge of true enforcement parameter levels and base their reporting strategies on perceived enforcement severity, social norms, and neighboring agent behavior. The authors devote the first part of their paper to developing an aggregate level compliance model, which uses differential equations to describe the flows of taxpayers from one group to another (e.g., the flow of honest taxpayers to cheaters). They build an agent model to supplement and verify the results of this macro–level to overcome the weakness of “making unrealistic assumptions” about the movements of taxpayers from group to group. Agents in their model update their beliefs about enforcement penalties over time. To initialize their agent model, Davis et al. (2003) randomly assign taxpayers into one of two classes—honest or evaders. Taxpayers are randomly assigned neighbors and honest taxpayers become “susceptible with some probability” to evading if they witness one of these randomly assigned neighbors not complying. The authors note two important findings generated by their agent model. First, they conclude that when dealing with mostly honest populations, the tax authority might use enforcement as a tool to prevent “evasion epidemics” rather than as a tool to “increase existing compliance.” Second, their agent model exhibits unstable equilibria that are characterized by sudden and dramatic shifts in behavior away from compliance, which should concern tax authorities.

NETWORKED AGENT COMPLIANCE SIMULATION MODEL (NACSM)

Most conventional models assume a representative agent approach, where one

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1 Bloomquist (2006) gives a comprehensive review and comparison of existing MABS compliance models.
agent’s characteristics are representative of the whole population. The researcher then proceeds to employ basic calculus to derive expressions describing an equilibrium amount of reported income or some optimal filing decision in general. Comparative statics are then used to examine the impact on this equilibrium outcome of changing enforcement parameters. Here we depart from this approach in several distinct and important ways. First, the agents in our model are heterogeneous. For example, they have different endowed beliefs or perceived risks about their chances of being audited or apprehended (given that they choose a non-filing path). That is, in our model agents make decisions based on perceptions—these perceptions are heterogeneous across agents. This stands in contrast to most tradition models that employ the representative agent approach and treat this agent as an immutable creature who never changes his perceptions or tastes.

Second, our model is populated by dynamic agents whose characteristics are updated and changed from period to period. Most traditional compliance models are not dynamic but instead use comparative statics to evaluate exogenous parameter changes.

Third, agents in our model exist in local social networks where they observe other agents’ payoffs to various compliance strategies. Neighbors’ payoffs can then affect an agent’s decisions when evaluating the compliance decision in the next period. Aside from some of the earlier-mentioned studies, researchers have more recently attempted to account for social influences on a taxpayer in a dynamic context. In the NACSM model, we model this social interaction explicitly by allowing agents not only to take into account their individual respective payoffs from pursuing a strategy, but also to factor in (to some degree) their neighbors’ payoffs.

The Taxpayer (Agent) Decision Process

When approaching the compliance decision at the beginning of each period, each agent in our model evaluates the associated expected payoffs, \( E_\text{r}[r] \), from pursuing three possible paths given by expressions [1]–[3]. The agent decision rule is to choose the path with the highest expected payoff, \( E^*[r] \). The parameter definitions for all the parameters that factor into the agent decision process are listed along with other important model parameters in Table 1.

Non-file—Do not file a return:

\[
E_{\text{NF}}[r] = q_i [Y_i (1 - \tau (1 + f)) - c_2] \\
+ (1 - q_i) Y_i.
\]

Underreport—File a return, but underreport income:

\[
E_{\text{FL}}[r] = p_i [Y_i - \tau X_i - c_1] \\
- \tau (Y_i - X_i)(1 + \theta) \\
+ (1 - p_i) [Y_i - \tau X_i - c_1].
\]

Report all—File a return and report all income:

\[
E_{\text{FH}}[r] = Y_i - \tau X_i - c_1.
\]

Agents in our model never know the true audit rate set by the tax authority. Instead, they are endowed with a perception of audit likelihood conditional on filing a return. We assume the perceived chance

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2 Researchers have noted that agents do not really know the true audit rate set by the tax authority, but rather act on perceived probabilities of audit or apprehension (Erard and Feinstein, 1994).

3 This assumption is consistent with the empirical findings of Erard and Feinstein (1994), who note that “taxpayers have substantial and varied misperceptions about the probability of audit.” However, Feld and Frey (2007, p. 103) note that “[i]ndividual misperception of risk is unsustainable over a longer time horizon, however, as people can infer control intensities from friends and relatives. Subjective probabilities of being caught exist, but they are most likely to be shaped by shared knowledge about the individual’s ability to evade taxes in different subgroups of the population.”
of being audited, \( p_i \in [0,1] \), is heterogeneous across the agent population. If for example an agent is endowed with a belief that he will surely be audited, then \( p_i = 1 \). After an initial randomly endowed \( p_i \), the agent’s perception of audit is modified according to the following rule in subsequent periods:

\[
p_{i}^{t} = p_{i}^{t-1} + \gamma (P_{i}^{O,t} - p_{i}^{t-1}) + \epsilon_{i}^{t}.
\]

In expression [4], \( P_{i}^{O,t} \) represents the agent’s observed audit rate from period \( t \). That is, an agent develops a perceived audit rate based on how many of his neighbors (including himself) were audited by the tax authority. If this observed audit rate exceeds the agent’s perceived audit probability from last period, then his new perceived audit probability will augment last period’s by some amount (\( \gamma \)) of the difference between last period’s perceived rate and observed rate. We call \( \gamma \) the rate of adaptation to the observed rate. Likewise, if the observed audit rate is less than the perceived audit rate, then the agent’s perceived audit probability for the next period will decline by \( \gamma \). If \( \gamma = 0 \), the agent ignores any observed audit information from his neighbors and perpetually sticks to his endowed perceived probability of audit.4

The next important feature of our model is to incorporate heterogeneous perceptions of risk among the agents. Thus, in addition to perceived audit likelihood, agents are endowed with a separate perceived risk of apprehension that is used when evaluating the expected payoff from non-filing a return. It is important to state explicitly that in our model we distinguish perceived apprehension risk, \( q_i \), from perceived audit probability, \( p_i \). As depicted by expression [1], we assume that an agent distinctly evaluates his odds of being apprehended when considering the non-filing route (i.e., the perceived probability of getting way with being an illegitimate non-filer). We adopt this approach from Erard and Ho (2001) who model the taxpayer compliance strategy as weighing the expected outcome of

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4 We also allow for the possibility of noisy observation of neighbors’ audit outcomes. That is, the model incorporates a noise parameter, \( \epsilon_{i}^{t} \), that influences the agent’s perceived audit rate. We assume that this agent–specific observation noise is drawn from a normal distribution; \( N_{\epsilon} \sim (0, 0.01) \). For this paper, we focus on demonstrating the overall function of the NACSM model and digress from examining the impact of noisy observation.
filing and reporting some amount of income versus the expected outcome from non-filing.\(^5\)

One way of interpreting \(q_i\) is also as an agent’s taste for risk. In our model, higher \(q_i\) means a lower taste for risk. Thus if we let \(\sigma_i\) represent an agent’s risk preference then \(\sigma_i = 1 - q_i\). This parameter also critically determines what portion of income an agent will report given that he files a return. Agents with greater tastes for risk report a lower share, \(s_i\), of their income according to \(s_i = \sigma_i\). Essentially, agents with a low perceived risk of apprehension are more likely to non-file or file and report a lower share of their true income. Agent perception of apprehension is initialized as a random draw from a uniform distribution on the interval [0,1].

At the end of each period, an agent evaluates the difference between his expected payoff, \(E[r]\), and the actual payoff, \(R_i\). In other words, agents formulate their respective compliance strategies based on expected payoffs, yet at the end of the tax period they each will know exactly which outcome occurred; e.g., was the agent audited, was he apprehended, or did he escape detection? Thus, after the taxpayer commits to a strategy, the tax period ends, and agents are randomly audited (or randomly apprehended if they decided not to file). The taxpayer then evaluates his actual payoff from the tax period and compares that with his expected payoff to develop what we call a relative payoff differential, \(D_i\), given by:

\[
D_i = \frac{R_i - E[r]}{E[r]}.
\]

The relative payoff is used to update the agent’s perceived risk of apprehension (\(q'_i\)) based on last period’s interactions (or lack of interaction) with the tax authority. In addition, we assume that an agent is able to observe his neighbor’s relative payoffs, and takes these into account as well. That is, \(q'_i\) changes from period to period. Specifically, we allow an agent to update his perceived risk of apprehension according to the following rule:

\[
q'_i = q^{-1}_i - \omega_i \cdot D^{-1}_i - \left((1 - \omega_i)/N_i\right) \sum_{j=1}^{N_i} D^{-1}_j + \nu'_i.
\]

This updating rule states that a taxpayer’s perception of risk is determined by three factors: 1) his realized relative payoff, \(D^{-1}_i\), from pursuing last period’s compliance strategy; 2) his neighbors’ realized relative payoffs from pursuing their respective strategies, \(D^{-1}_j\); and 3) an agent-period specific noise component, \(\nu'_i\), that affects how he learns his neighbors outcomes (noisy observation of neighbors).

When updating his perceived risk, an agent weights by some amount, \(\omega_i\), his prior period payoff, \(D^{−1}_i\), and weights his neighbors’ payoffs, \((1 - \omega_i)/N_i \cdot D^{−1}_j\), where \(N_i\) is the size of the agent’s neighborhood, and \(D^{−1}_j\) is the \(j\)th neighbor’s relative payoff (\(i \neq j\)). Thus, when updating his perceived risk, an agent factors in his personal experience with the tax authority, as well as some noisy, weighted knowledge of his neighbors’ outcomes. Figure 1 illustrates the complete agent compliance decision process.

**Social Network Structure**

As each agent exists in a social network, we briefly describe the structure of this network. First, the NACSM model gives us flexibility in how we construct our social networks. The entire agent landscape exists as a square (two-dimensional) lattice structure. We assume that

\(^5\) Erard and Ho (2001) outline a theoretical compliance strategy model where probability of audit and probability of apprehension are separate.
an agent has eight neighbors and is, thus, what is known as a Moore neighborhood. Figure 2 depicts this network structure. We assume that the Moore neighborhood is of range $n = 1$, so that an agent’s neighborhood size can be up to nine agents (including the agent). In this type of network, to be considered as a neighbor, an agent must share some bordering space (even a corner border, e.g., the states of Colorado and Arizona would be Moore neighbors.). Note that agent one’s neighbors are agents two through nine; agent eight is a neighbor of both agents one and 12, but agents 12 and one are not neighbors to one another. Moreover, the landscape is toroidal, meaning that the entire landscape is doughnut-shaped so that, for example, agent 16 has agents 23 through 25 as neighbors.

**MODEL RESULTS**

The first simulation we show using the NACSM model is to compare the results of an initial set of enforcement parameters in a world that has no social networks. We then show three counterfactual simulations; the first (scenario 1), where agents partially factor in the payoffs of their neighbors, $\omega_i = 0.5$; the second (scenario 2), where agents put almost no weight on their individual respective payoffs, $\omega_i = 0.01$; and the last (scenario 3), where agent weights on their neighbors’ payoffs are randomly, uniformly distributed ($\omega_i \in (0,1)$), i.e., a world where some agents are heavily influenced by neighbors, while others pay only some attention to neighbors, while still others almost completely ignore their respectively neighbors payoffs.Initialized

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6 The number of agents in a Moore neighborhood of range $n$ is given by $(2n + 1)^2$.  

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parameter values are exhibited in Table 2. The gray boxes indicate parameters that do not change across the simulations.

Figures 3 through 5, respectively, display the percentage of compliant agents, the percentage of non–filers, and the tax gap under the baseline and three different scenarios. We present the aggregate percent of compliant or “near” full compliant agents. (We use a threshold of a minimum of 95 percent reported true income reported to be considered “near” full compliance.) In these three scenarios, including the baseline, the true audit and apprehension probability is constant from period to period (a two percent probability of audit or apprehension given evasion). Our measure of the tax gap is actually the net tax gap; thus it includes tax obligations and penalties collected from enforcement.

One noticeable difference in the scenarios is the high level of compliance that emerges in the baseline simulation (no social networks) with relatively low enforcement parameter settings. However, the more agents begin to factor in the payoffs of other agents (at a given a level of enforcement), measures of compliance evolve at lower levels. In fact, the more agents weight other agents’ payoffs, compliance drops off dramatically. For example, in a society where agents put almost no weight on themselves, i.e., a society where agents are completely impressionable and care nothing of their own individual payoffs, compliance completely deteriorates. In this world, scenario 3, the number of non–filers stabilizes in a range that fluctuates between 60–70 percent of the agent population (Figure 4), while the tax gap hovers around 90 percent.

<table>
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<th>TABLE 2</th>
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<td>BASELINE SIMULATION SETTINGS</td>
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<td>Model Settings</td>
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<td>Agents</td>
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Figure 3. Different Weightings on Neighbor Payoffs: Compliant Agents

Figure 4. Different Weightings on Neighbor Payoffs: Non-Filing Agents
Notice that after the initialization period, each metric begins to exhibit convergence to an equilibrium level. For example, the baseline agent simulation exhibits a non-linear convergence to a society with mostly compliant taxpayers (about 90 percent compliance). This convergence path, from a macroscopic point of view, is relatively “smooth” with some deviation from period to period in the number of compliant agents. Moreover, the rate of convergence is faster in the first half of the exhibited time frame ($t < 500$) and slows as it approaches about 90 percent. However, beneath this macroscopic perspective is regional variation in our metrics and ultimately somewhat chaotic–appearing intertemporal behavior of the agents themselves. Using the tax gap as our compliance metric, Figures 6 and 7 each display a set of charts that exhibits this phenomena. Each of the three charts represents an increasingly micro–level view of agent behavior. The macro level view is presented as the aggregate tax gap. As noted earlier, the agent world with no social networks converges to compliance much faster than the world where agents are heterogeneous in how they factor in neighbor payoffs to their risk adjustments.

The second row of charts in Figures 6 and 7 represents the regional–level perspective of agent behavior—a mesoscopic–level view. In Figure 6.2, there is variation in regional levels of compliance from period to period, though all regions trend toward higher compliance as measured by a lower tax gap. In Figure 7.2, (scenario 4), there is an apparent greater degree in variation among the three sampled regions. Moreover, while

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7 Here we use the term mesoscopic to refer to the level between the macroscopic world and the individual agent (atomistic) level of behavior. The NACSM model has 16 different regions, but we only present three in these charts for demonstrative purposes.
Figure 6. Tax Gap, No Social Network

1. Aggregate Tax Gap

2. Regional Tax Gap

3. Agent Reported Income
Figure 7. Tax Gap, With Social Networks

1. Aggregate Tax Gap

2. Regional Tax Gap

3. Agent Reported Income
two of the regions appear to have a flat
to slightly increasing tax gap, the third
appears to have a tax gap that is shrink-
ing over time.

Finally, we drill down further to the
microscopic, atomistic level of society—the
agents themselves. While we cannot show
every agent, we randomly sampled three
agents from each simulation to examine
reported income—the agent level tax gap.
In both Figures 6.3 and 7.3 the displayed
sample agents exhibit seemingly chaotic
compliance paths over the course of the
respective simulations, though the sample
agents from the baseline simulation do
appear to tend towards higher compli-
ance over time. This final–level view,
however, demonstrates something inter-
esting regarding both social networks and
ABM in general. Specifically, we see that
the overall emergent pattern of aggregate
compliance between Figure–sets 6 and 7
is very different; the baseline run, with
no social networks, converges toward
a highly compliant society, whereas
scenario 4 (agent heterogeneity on the
weighting of social networks) converges
to a lower level of compliance. However,
at the microscopic level, both simulations
highlight the dynamic and seemingly
chaotic period–to–period behavior of
the agents, yet for the same given set of
enforcement parameters, the aggregate
outcomes are very different.

**Stability of Equilibria under Change
in Enforcement Regimes**

Next we examine the stability of equi-
libria in the face of an enforcement regime
change. To carry this out, we implement
two simulations where there is a change in
the enforcement regime after convergence
to equilibrium compliance levels (given
a set of initial enforcement parameters).
We then use the graphic output of the
NACSM model to display results. In
each simulation, we set the initial audit
and apprehension rates to ten percent,
and set penalties and fines to 75 percent.
After each simulation has stabilized to
equilibrium, we reduce the penalties and
fines on underreporting and noncompli-
ance respectively to 20 percent. Then we
examine how this enforcement regime
switch affects the stability of the compli-
ance level equilibrium in each simula-
tion.

The first simulation—the “baseline”
simulation (Figure 8)—is a society in
which agents do not factor in at all the
payoffs of their neighbors—they are
unimpressed by positive or negative
impacts to a neighbor’s compliance
strategy. The second simulation—what
we will call the “impressionable agent
scenario”—is a society in which agents do
take into account the payoffs to neighbors’
compliance strategies, but as in the earlier
“scenario 4,” each of the agent weightings
on neighbor payoffs is heterogeneous.
Rather than exhibit the output in a graphi-
cal format, we qualitatively examine
results using the output, “heat–map”
type displays of the NACSM model. The
agents are represented by each box (just as
described in Figure 2). The color codes are
necessary to understand the results. Black
represents a non–filer; dark gray
represents
an agent below the low–filing threshold
(reporting under five percent of income);
white represents agents who report all
income or almost all of their income (no
greater than five percent unreported);
and gray represents under–reporters
who are between the low– and high–fil-
ing thresholds. Where an agent has been
audited or apprehended, an “×” appears
in the agent’s square on the displayed
lattice.

In Figures 8 and 9, the enforcement
regime change was made between frames
3 and 4. Thus, each simulation was
stopped after convergence to an equilib-
rium state and then the fines and penalties
were decreased. As shown in Figure 8, in
the baseline simulation—where agents
ignore neighbors’ payoffs—there is no
Figure 8. Agents Disregard Neighbors Compliance Strategy Payoffs
Figure 9. Agents Consider Neighbor Payoffs. (Heterogeneous Weights on Payoffs)
perceivable change in compliance across the agent landscape when penalties are lowered. The society is highly compliant, and this equilibrium appears to be stable and robust to our enforcement regime change. However, the impressionable agent scenario exhibits vastly different outcomes. After converging to a highly compliant equilibrium, the reduction in penalties and fines spurs an increased amount of noncompliant behavior as exhibited by the local emergence of hot-spots—enclaves of non-compliance signified by black and dark gray. Some regions do not show this flare in non-compliant behavior and, thus, remain white; however, as the bottom three frames in Figure 9 show, the noncompliant activity appears to be spreading in an epidemic-like fashion. Thus, in the impressionable agent scenario, the original equilibrium was not robust to an enforcement regime change, and in fact shows how in a society where agents weight the payoffs of others (even heterogeneously), noncompliant activity can still spread in epidemic-like fashion, undoing a seemingly stable, highly compliant equilibrium.

The Impact of Different Fines and Penalties

The next set of simulations that we display explores aggregate compliance outcomes holding all parameters constant except for penalties and fines. The first chart (Figure 10) exhibits the impact of different fines and penalty levels on various measures of compliance. (We hold the audit and apprehension probability constant at two percent, and use the same settings given earlier in Table 2). Next, two simulation sets are implemented: the first simulation set (baseline) considers a world where agents do not factor in neighbor compliance strategy payoffs; the next set of simulations (impressionable agent scenario) allows for heterogeneity across agents in the manner in which they weight neighbors' payoffs. The penalty and fines are increased by ten percent in each simulation. The results in Figures 10.1 and 10.2 suggest that penalty and fines have different impacts in the two societies. Figure 10.1 shows the results from a world where neighbor payoffs are not factored into agent decisions. As fines and penalties increase, compliance, as measured by the percent of the population electing the non-filing route and the size of the tax gap, decreases at a constant rate until an almost fully compliant society is reached between fines and penalties of 20 and 30 percent. The number of under-reporters (shown as a percent of the population) falls as well, albeit more slowly. (Under-reporters are actually reporting more income as the penalties and fines increase, thus also contributing to the closing the tax gap.)

Figure 10.2, on the other hand, points to a highly nonlinear relationship between aggregate compliance and penalties. As fines and penalties increase, the non-filers appear to transition to under-reporting. And though the number of under-reporters is high at higher levels of fines and penalties, most of these under-reporters are almost compliant—reporting at least 95 percent of their income. The marginal impact of changes in penalties on compliance seems greatest in the range between ten and 40 percent, with an apparent point of inflection at 20 percent where the marginal impact of penalties on compliance begins to decrease. Marginal changes in fines and penalties at high levels (greater than 50 percent) appear to have

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8 Though we distinguish between fines on non-filer income and penalties on the under-reported income of filers, we keep these rates equivalent in these simulations. We could easily allow for these rates to differ to test, for example, for equilibrium outcomes where penalties and fines differ greatly from one another.
Figure 10. Compliance Metrics Over Range of Fines and Penalties

1. Neighbor Payoffs Not Considered

2. Neighbor Payoffs Considered (Impressionable Agents)
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minimal impacts on compliance in both worlds.

Compliance and Neighbor Payoff Weightings

The last set of simulations explores the impact of different agent payoff weightings ($\omega$) for a given set of enforcement parameters. That is, what are equilibrium compliance outcomes given societies where agents weight their neighbors’ payoffs highly in their individual decisions versus outcomes where agents ignore neighbor payoffs? In this set of simulations, we set the audit and apprehension rate to two percent and set fines and penalties to 50 percent. The results are displayed in Figure 11.

As agents weight neighbors’ payoffs more (moving from right to left along the horizontal axis), the overall level of compliance decreases. The most interesting feature of this chart is that there appears to be a tipping point between 0.20 and 0.40, i.e., a point where aggregate compliance changes dramatically given a small change in $\omega$. The tax gap appears to be stable and small for $\omega$ above 0.40, but this highly compliant equilibrium collapses rapidly when agents begin to weight their personal compliance strategy payoffs lower (below 40 percent) relative to the payoffs of those in their social network. Thus, moving from right to left, the tax gap and associated number of non–filers grows rapidly. Also notice that (again moving from right to left) prior to the collapse of this compliant equilibrium at a $\omega$ of 0.4, the number of under–reporters increases steadily peaks and at about 0.4, and then declines rapidly as many of the under–reporters convert to non–filers. Furthermore, there is a peculiarity where $\omega = 0.20$; the number non–filers begins to decline as these agents convert from non–filing to under–reporting as $\omega$ shrinks to zero.

Figure 11. Compliance Metrics Over Range of Agent Payoff Weights
CONCLUSIONS

In this paper we sought to apply a relatively new approach to the long-standing social issue of tax noncompliance—agent-based modeling. The strength and capability of this approach in addressing the tax compliance phenomena is that such models are flexible in accommodating heterogeneity among a society of interacting agents—features not common in more traditional simulation approaches.

Second we were able to generate highly compliant equilibria with low rates of enforcement (an outcome not witnessed with the conventional A&S models). Yet, when we drilled down to the atomistic agent level of society, we witnessed great diversity in agent period-to-period compliance strategies. From year to year, some agents under-report, some do not file, and some remain persistently compliant. Specifically, dynamics at the agent level appear almost chaotic, yet an aggregate, predominantly compliant equilibrium can emerge.

Third, and perhaps the most important feature of our research as it relates to tax compliance, is the incorporation of networked agents who share compliance strategy payoff information. This structure was used to demonstrate that when agents weight neighbors’ payoffs more heavily in their compliance strategy decisions, i.e., they become more impressionable, non-compliance tends to increase. We are then left to ask why this might obtain. The inductive conclusion might start with the fact that with low enforcement (similar to reality), some agents will always successfully evade each period. But this alone is not what causes a disintegration of aggregate compliance in our model. The path toward noncompliant equilibria is determined by agent impressionability (what Davis et al. (2003) would call “susceptibility”). In our model, the degree, $\omega$, to which agents allow their neighbors’ payoffs to influence their decisions determines the path to a compliant or noncompliant equilibria. The more agents weight their neighbor’s outcomes, the less compliant our society becomes for given levels of enforcement. Conversely stated, with low levels of enforcement in a society where agents pay little attention to their neighbors’ payoffs, aggregate compliance emerges very rapidly. Thus, one preliminary result of the NACSM model is to suggest that having a society of taxpayers who largely disregard the monetary payoffs of evaders is sufficient to generate aggregate compliance at low levels of enforcement.

We acknowledge that in reality taxpayers likely do not share “payoff” information en masse. If a taxpayer pursued a particular scheme or evaded his tax obligations in some way, his social network counterparts may never know the gains made from pursuing a certain path. However, we know that illegal tax schemes exist and that such noncompliant propaganda can be transmitted by networks of people who have some shared social characteristic (e.g., same profession, same tax preparer, etc.) Thus, we used our model’s “heat-map” display to show how pockets of noncompliance can flare up when enforcement parameters are decreased.

Finally, we briefly point to some potential areas of future research. First, the NACSM model presents a rich environment with which to study compliance under different enforcement regimes and with different social network structures. We used a very limited amount of its overall capability, yet we demonstrated results that would be very difficult for conventional models to tackle. However, the NACSM model could be used and modified to investigate the social network aspect of compliance further. For example, we could examine interactive enforcement strategies that are developed based upon evolving agent behavior. Furthermore
the agents themselves can be made more intelligent by allowing for the endogenous development of new compliance strategies, which could be shared among agents. In addition, agents could be endowed with properties that capture prevailing social norms.

In general, using the computational modeling approach to understand tax compliance is only at its beginning stages. This method can also be a powerful complement to the ongoing work in experimental economics where human participants engage in scenarios that mimic the compliance process (see Alm and McKee (1998)). In fact, one potential avenue of research might use the data and results from experimental studies of compliance to calibrate the properties of our agents. Building on this idea, one might do an experiment where agents and human subjects are intermingled in the same laboratory environment. One could then analyze the resulting experimental data to see if artificial agents behave differently than human subjects. These results might then be used to further calibrate a larger-scale, higher-fidelity agent model, which could generate useful insights regarding taxpayer responses to enforcement regime changes.

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