A Large-Scale Agent-Based Model of Taxpayer Reporting Compliance

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Abstract. This paper describes the development of the Individual Reporting Compliance Model (IRCM), an agent-based model for simulating tax reporting compliance in a community of 85,000 U.S. taxpayers. Design features include detailed tax return characteristics, taxpayer learning, social networks, and tax agency enforcement measures. In order to comply with rules prohibiting the disclosure of taxpayer information, artificial taxpayers are created using data from the Statistics of Income (SOI) Public Use File (PUF). Misreported amounts for major income and offset items are imputed to tax returns based on examination results from random taxpayer audits. IRCM is programmed in Java using the Repast Simphony agent-based modeling and simulation toolkit. A hypothetical simulation illustrates a potential use of the model.

Keywords. Tax compliance, tax gap, agent-based modeling, Repast, MASON.

1 Introduction

In tax year (TY) 2006, the U.S. Internal Revenue Service (IRS) estimates the gross tax gap – the true amount of tax due but not paid voluntarily and timely – was $450 billion, representing 16.9 percent of the total tax due from individuals and corporations [1]. The loss of revenue associated with the tax gap is a burden that falls disproportionately on compliant taxpayers and contributes to the nation's budget deficit. Consequently, finding ways to reduce the tax gap is an ongoing concern for the IRS.

Research on individuals' motives for complying with tax laws has flourished since the 1972 publication of Allingham and Sandmo's [2] groundbreaking theoretical work on the subject.[1] However, this vast body of knowledge has not been successfully integrated into computational tools that could help tax administrators improve taxpayer compliance. The lack of progress on applications development stems from researchers' inability to incorporate sufficient realism into theoretical models of taxpayer be-

[1] Surveys of the tax compliance literature are found in [3-6].

havior [4]. The realization that analytical methods are often inadequate for modeling complex social phenomena has led to the growing interest in agent-based modeling [7-9].

During the last decade a number of agent-based models (ABMs) of taxpayer compliance have appeared in the literature [10-20]. Mainly exploratory in nature, these models lack the degree of realism required for applied use, such as a detailed representation of income reporting requirements and key institutional relationships linking taxpayers, tax preparers, employers and the tax agency. This paper introduces a model that addresses many of these operational deficiencies.

This paper describes the design and implementation of the Individual Reporting Compliance Model (IRCM), an ABM that simulates the income tax reporting behavior of a community of 85,000 individual taxpayers. The IRCM (or the "model") includes many enforcement mechanisms used by tax agencies, such as audits and information reporting, as well as detailed information on the reporting compliance for major income and offset items. A point-and-click interface allows the user to easily explore the impact on taxpayer reporting compliance of alternative assumptions concerning tax agency enforcement and information reporting. In order to comply with IRS disclosure rules no taxpayer data is used. Instead, a dataset of artificial taxpayers is created by selecting cases (with replacement) from the Statistics of Income (SOI) Public Use File (PUF) [21] that are close statistical matches for actual tax returns. The model is written in Java and uses Repast Simphony [22] software libraries for random number generation and chart production. Finally, the model design allows for new information about taxpayer behavior to be incorporated as such information becomes available.

The outline of this paper is as follows. Section two gives an overview of the IRCM framework and describes agents and agent behaviors. Section three describes the steps involved in constructing the dataset of artificial taxpayers used by the model. Section four discusses model validation and calibration. Section five presents a hypothetical case study analyzed using IRCM. Section six concludes and highlights topics for further research.

2 Model Description

2.1 Agents

Figure 1 graphically displays the IRCM agent architecture. A single *Region* is composed of multiple non-overlapping zones. Each *Zone* represents the place of residence for a group of filers (e.g., a postal zip code zone). Each *Zone* also has a list of all tax preparers and employers located within its borders. A *Preparer* agent prepares tax returns for its clients. *Employer* agents represent firms having one or more employees. Form 1040 filers are represented by *Filer* agents. A tax return is an instance of the *TaxReturn* class. All tax returns are reviewed by a tax agency (an instance of the *TaxAgency* class) and are subject to a possible audit. The tax agency selects filers for audit using one of three user-specified audit strategies: random, fixed proportion, and constrained maximum yield (CMY). The CMY audit selection strategy uses a simple learning algorithm to incrementally improve overall yield per return audited.

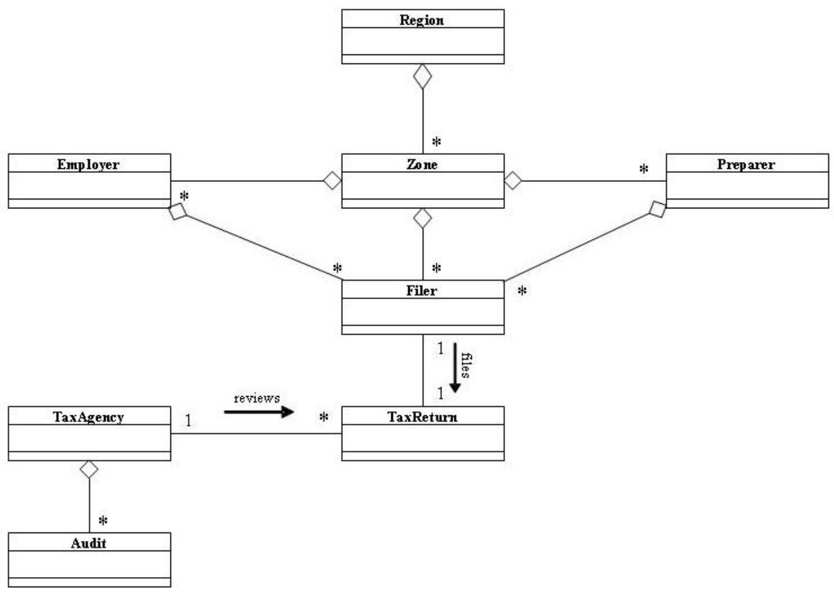

Fig. 1. IRCM Agent Hierarchy

The interaction between filers and the tax agency is illustrated in Figure 2. The filer either uses a paid preparer or self-prepares. The tax agency reviews the return and determines if any discrepancies are present on items with third-party information reporting (e.g., Form W-2 for wage and salary income). If the return is audited the amount misreported is recorded. If not audited, the filer decides how much income to report in the next period for items with little or no third-party information reporting. If audited, the filer may reevaluate reporting on all major income and offset items.

2.2 Model Execution

The steps followed in executing a simulation using IRCM are shown in Figure 3. The model reads tax return data for the population of artificial taxpayers and instantiates agents. During instantiation, IRCM estimates a true amount for the most important Form 1040 income and offset items which is defined as the reported amount plus imputed misreporting.[2] Imputed amounts are based on audit results from the TY 2001

2 Imputed income items are: wages, interest, dividends, state tax refunds, alimony, sole proprietor income (Schedule C), capital gains income (Schedule D), other gains (Form 4797), individual retirement account (IRA) income, pension income, supplemental income (Schedule E), farm income (Schedule F), unemployment compensation, social security and other income. Imputed offset items are: adjustments, deductions, exemptions and statutory credits

National Research Program (NRP) study. Details of the imputation methodology are described in [24].

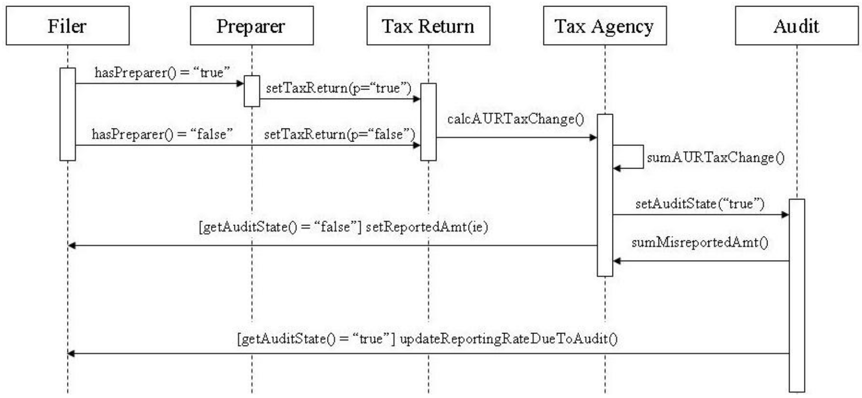

Fig. 2. Interaction Between Filer and Tax Agency

Each time step represents one filing cycle (year). Tax calculations are performed twice for all taxpayers, once using reported amounts and again using estimated true amounts. The difference in calculated tax using true and reported amounts is the tax gap for each filer. By default, IRCM assumes the difference between the true and reported tax amounts is the amount identified by the tax auditor. An option is provided to account for underreporting not detected by examiners.[3]

Tax audits are performed at the penultimate step in each time loop. During wrap up, the tax agency issues Automated Underreporter (AUR) notices to taxpayers who are not audited but where computer checking of tax returns against information documents detects some underreporting.[4] In addition, filers who stop filing, either because they leave the region or no longer have an obligation to file, are replaced by a new filer having identical income and network relationships as the "stop filer" being replaced, but with reporting behavior and memory reset to baseline levels (i.e., no memory of a prior audit experience or audits of reference group members, if that option is selected). The reporting behavior of filers who are not "stop filers" is also updated at each time step, as is the audit selection strategy of the tax agency. Finally, data collection occurs during the wrap-up phase. When the user-specified number of time steps has completed the model generates output in the form of tables and charts that can be reviewed and saved for further analysis.

(net the Child Tax Credit). Adjustments to certain credits (e.g., Child Tax Credit, Earned Income Credit and Additional Child Tax Credit) that reflect a change in income are performed by a tax calculator. Each tax return consists of 180 elements based on the PUF data.

3 This is done by applying multipliers to positive detected misreported amounts; that is, misreporting in the taxpayer's favor. See [25] for the Detection Controlled Estimation (DCE) methodology used to derive the multipliers used by IRCM.

4 The threshold amount for issuing an AUR notice is set by the user. The default value is $1.

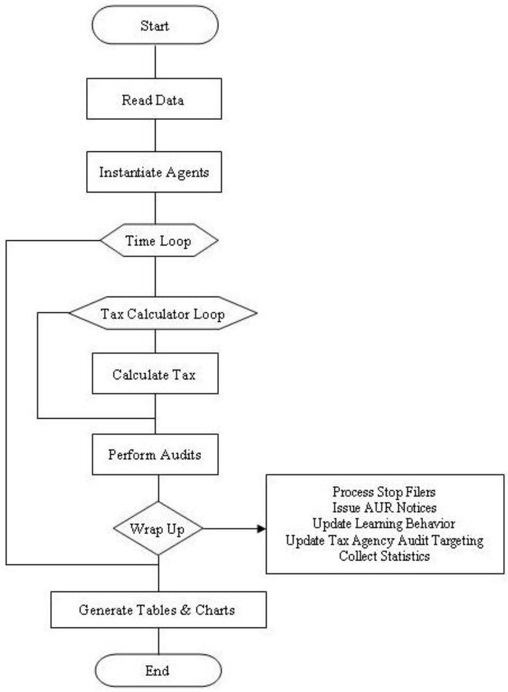

Fig. 3. IRCM Execution Sequence: Top-Level View

2.3 Filer Response to a Tax Audit

Following Gemmell and Ratto [26] a filer's response to a tax audit is based on user-supplied probabilities that cover two mutually-exclusive states (selected for a tax audit or not selected) and four response categories (perfect compliance, increase compliance, decrease compliance and no change). Since taxpayers do not know with certainty that taking a specific action will result in being selected for a tax audit, this problem is classified as a partially observable Markov decision process (POMDP) [27]. A POMDP is a 5-tuple $\Sigma = (S, A, P, C, O)$, where

- S is a finite set of states
- A is a finite set of actions
- P is a probability distribution where for each $s \in S$, if there exists $a \in A$ and $s' \in S$ such that $P_a(s' \mid s) \neq 0$, we have $\sum_{s' \in S} P(s, a, s') = 1$.
- $C_a(s, s')$ is the cost/reward (or expected cost/reward) experienced from transition to state s' from state s with transition probability $P_a(s' \mid s)$. The quantity $P_a(s' \mid s)$ is the probability that if action a is executed in state s, then state s' will result. For example, if a taxpayer decides to increase compliance following a tax audit,

one can infer that the action is being taken in order to reduce the probability of being selected for an audit (and the associated costs) in future time periods.

- O is a set of observations with probabilities $P_a(o \mid s)$, for any $a \in A$, $s \in S$ and $o \in O$. $P_a(o \mid s)$ represents the probability of observing o in state s after executing action a. Finally, it is required that the sum of probabilities over the set of observations is 1, i.e., $\sum_{o \in O} P_a(o \mid s) = 1$.

Since the observations in a POMDP represent probability distributions, rather than exact states of the system, the probability distributions are called *belief states* and are updated using Bayes Rule. The use of Bayes Rule implies that the probabilities represented by $P_a(o \mid s)$ are not static but change as knowledge of the enforcement environment changes.

In IRCM neither the belief states (O) nor the cost functions (C) of individual filers are modeled explicitly but are implied in the stochastically driven "choices" made by filers. This approach is taken since, at present, so little empirical data is available to indicate about how taxpayers perceive the tax enforcement environment or the specific causes that motivate changes in observed behavior. However, modeling filers' response to audits as a stochastic process is supported by observed behavior in tax compliance laboratory experiments [4].

Figure 4 graphically illustrates the POMDP portraying a filer's response to a tax audit. The two states are not audited (S_0) and audited (S_1). The filer's belief about the probability of audit is defined as $r_{a_k} = b(r \mid a_k)$ which implies that the filer's perceived probability of being selected for a tax audit depends on his or her belief about how the baseline audit probability (r) changes with a change in reporting behavior (action) a_k.

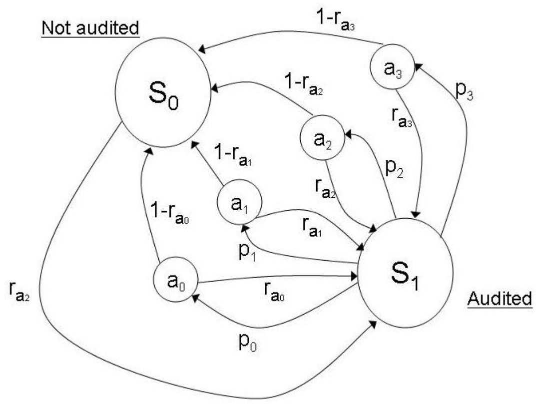

Fig. 4. POMDP of the Filer's Response to the Tax Audit Environment

In Figure 4 it is assumed $a_0 \equiv$ no change in reporting compliance, $a_1 \equiv$ an increase in reporting compliance, $a_2 \equiv$ decrease in reporting compliance and $a_3 \equiv$ perfect reporting compliance. If not audited in time t the filer may start or increase underreporting in time $t+1$ on income subject to little or no information reporting, assuming the filer has such income from one or more sources. If the filer is audited in time t, the decision to select action $a_0 \dots a_3$ is determined in IRCM by a random draw and the user-specified probabilities $p_0 \dots p_3$. Although IRCM models the filer's response as a stochastic process, actual filers are presumed to select an action a_k based on their (heterogeneous and non-stationary) beliefs about the expected cost associated with that action.

2.4 User Interface

Figure 5 displays the IRCM's main screen where the user defines the baseline and alternative scenarios, launches simulations, and views output for the region and zones.[5] Zones can be displayed with different characteristics including the number of filers, average reported income, and tax compliance rate. Tables summarizing key measures can be displayed for the entire region or for individual zones. From these tables the user can drill-down to the level of individual employers and tax preparers located within the selected area. This capability is useful for model verification and to investigate the spatial variation in filing and compliance behavior.

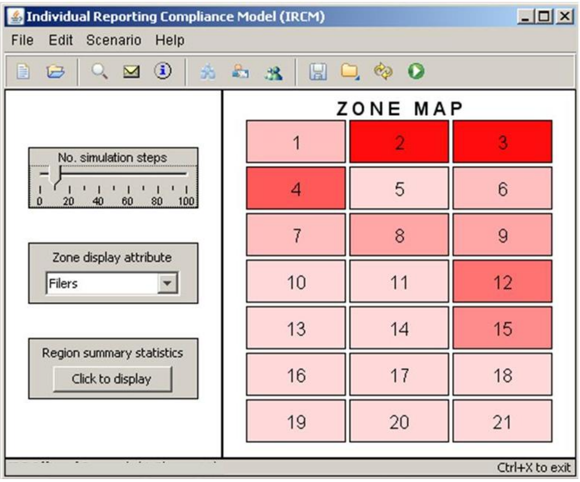

Fig. 5. IRCM Main Screen

3 Study Area Selection and Artificial Taxpayer Data

The area selected as the test-bed region is a single county with 85,000 individual tax filers in TY 2001. The region was selected based on its overall similarity to the nation on key economic and demographic characteristics (e.g., age structure, industry

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5 IRCM also generates output in the form of tables and figures which can be saved or exported to other applications for further analysis.

structure, racial composition, per capita income, etc.) as well as number of filers, which is sufficiently small to be modeled on a personal computer. In order to preserve taxpayer anonymity yet allow for independent verification and validation, the model is implemented using a dataset of artificial taxpayers. The basic idea in creating a dataset of artificial taxpayers is to substitute cases from the 2001 Statistics of Income (SOI) Public Use File (PUF)[6] for actual tax returns of individual filers in the study area. Although most fields in the PUF are derived from tax forms, SOI modifies the data in order to protect the identity of individuals. The statistical matching procedure used to create the database of artificial taxpayers is described in detail in [24].

4 Model Validation and Calibration

A two-stage approach is used to validate and calibrate the IRCM. In stage 1 (validation) the model is executed using values from the PUF (the "SOI reporting regime" option) and output is compared to IRS estimates of reporting noncompliance published tax gap studies. The method of comparison follows the cumulative approach of Axtell and Epstein [28]. They propose a hierarchy of four levels at which an ABM can be validated. A model with Level 0 validity is considered to be a caricature of reality. At this level the model needs to show only that the system as a whole exhibits behavior that is consistent with the available data (e.g., the aggregate response of agents to changing environmental conditions is in the appropriate direction). At Level 1 the model is expected to be in qualitative agreement with empirical macro-structures. This is demonstrated by comparing the distributional characteristics of the actual population to the modeled population. To be valid at Level 2 the model must show quantitative agreement with empirical macro-structures. Finally, at Level 3 the model exhibits quantitative agreement with empirical micro-structures, as determined from cross-sectional and longitudinal analysis of the agent population. IRCM's on-board graphical and statistical routines are used to demonstrate model validity through Level 2 [24]. Validation at Level 3 requires panel data on individuals' tax reporting behavior, which is a standard not yet available to researchers.

The goal in stage 2 (calibration) is to find a combination of values for the six "rule-based reporting regime" parameters[7] that can closely replicate IRCM output using the "SOI reporting regime" option. Formally, we want to minimize the sum of differences in reported incomes between the SOI and rule-based reporting regimes:

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[6] The 2001 PUF [21] is a stratified probability sample containing records for 143,221 tax returns.

[7] The six rule-based reporting regime parameters are: the percentage of filers that perceive misreporting can succeed on line items with none, some, and substantial information reporting, the marginal compliance impact of tax withholding, the percentage of deontological filers, and the *de minimis* threshold amount for reporting. Deontological filers are filers who comply out of a sense of "duty" [29], in contrast to the standard model of rational utility maximization [2].

$$\min \sum_i \left(\Lambda_i^{RB} - \Lambda_i^{SOI} \right) \tag{1}$$

In expression (1), Λ_i^{RB} is the calculated reported amount using the rule-based reporting regime in IRCM for income type *i* and Λ_i^{SOI} is the calculated reported amount for income type *i* using the SOI reporting regime. A solution for expression (1) is found by inspection using multi-stage Monte Carlo simulation, the details of which are described in [24].

5 Case Study

This section presents a simulation experiment that shows how the IRCM can be used to assess the impact on taxpayer compliance of alternative audit case selection strategies. For this experiment the IRCM is executed using the rule-based reporting regime option with default values for the six parameters. In addition, it is assumed that if taxpayer *j* is audited then each of *j*'s neighbors or co-workers have a 25 percent chance of increasing their compliance, a 25 percent chance of decreasing their compliance and a 50 percent chance of no change.[8] Both coworker and neighbor reference groups are assumed to have a fixed size of five members.[9] Default values were used for all other model options.

Table 1 displays the output from IRCM for four alternative audit allocation strategies.[10] The strategy labeled "Random" is the baseline for comparing all other strategies and represents the direct effect (Audit Results), total misreported tax, and no change rate when individuals are randomly selected for a tax audit. Strategy 1 represents a slight improvement over the Random strategy by assigning more audits to groups of taxpayers with the highest average expected yield while not auditing more than one percent of taxpayers in a given audit class.[11] Strategy 2 is similar to Strategy 1 but has no fixed constraint on the maximum coverage rate for audit classes. This strategy has the largest direct tax change ($2,739,000) and the lowest no change rate. However, this strategy also has the lowest deterrence multiplier (1.5), which indicates that indirect effects (i.e., a change in compliance behavior of audited taxpayers in subsequent time periods and "contagion" effects via social networks) account for a relatively small share of the total compliance impact. Finally, Strategy 3

[8] In IRCM reporting compliance can decrease on line items with some or no information reporting but not on items with substantial information reporting. Compliance is allowed to increase on all line items.

[9] For employers with fewer than six employees but more than 1 employee, the coworker reference group size is N – 1 where N is the number of employees.

[10] The data shown represent average values for five independent simulations using different seeds for IRCM's random number generator. Each simulation was run for 300 time steps. The values for the last 50 time steps were used in computing the values shown in Table 1.

[11] IRCM has 17 pre-defined non-overlapping audit classes for return selection when random selection is not used.

allows up to a 10 percent coverage rate within an audit class but also requires a minimum of five audits for each audit class to ensure a minimum level of coverage for all taxpayers. This strategy results in somewhat lower direct effects and higher no change rate (compared to Strategy 2) but a higher overall reduction in misreported tax. The larger reduction in misreported tax for Strategy 3 is due to a larger indirect effect since this strategy affects a broader segment of the taxpayer population.

Table 1. Comparing Alternative Audit Allocation Strategies

	Audit Results ($1000)		Misreported Tax ($1000)			No
					Deterrence	Change
Scenario	**Total**	**Change**	**Total**	**Reduction**	**Multiplier**	**Rate**
Random	$252		$95,114			76.4%
1	$513	$262	$94,195	$919	3.5	65.2%
2	$2,991	$2,739	$91,017	$4,097	1.5	36.9%
3	$2,459	$2,207	$89,789	$5,325	2.4	42.9%

Figure 6 displays the time series of the average tax Net Misreporting Percentage (NMP)[12] of these five simulation runs for the four audit selection strategies. Based on visual inspection, the model reaches a stochastically stable solution for all strategies after about 250 time steps. Using the simulation output for the last 50 time steps, the random audit selection strategy has the highest tax NMP at 15.1 percent. Strategy 1 is the next highest with a tax NMP of 15.0 percent. The NMP for the Strategy 2 is 14.5 percent. Strategy 3 has the lowest average tax NMP (highest voluntary compliance) at 14.3 percent.

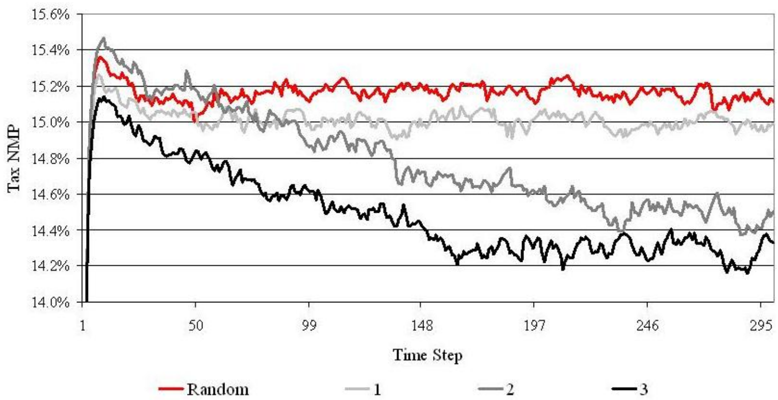

Fig. 6. Model Time Series of Tax NMPs for Alternative Audit Selection Strategies

[12] The NMP is defined as the net amount misreported in the taxpayer's favor divided by the sum of the absolute values of the amounts that should have been reported.

6 Conclusion and Future Research

The development of the IRCM demonstrates that agent-based simulation is able to model the complexities of real-world tax systems, such as differences in reporting compliance at the line item level and taxpayers' heterogeneous response behaviors, which researchers have found difficult to incorporate in analytical models of taxpayer reporting behavior [4]. The value of having a model like the IRCM grows as our knowledge of taxpayer behavior improves. Therefore, an important component to future development and use of ABMs for tax administration is an ongoing program of research to further identify and restrict, as appropriate, the behavioral parameters used in such models. Such a research program must necessarily employ a range of data collection methodologies as appropriate including laboratory experiments, field studies, and surveys.

Presently, the IRCM is undergoing independent verification and validation testing by analysts at The MITRE Corporation. The model has been ported successfully to both Windows and Mac-OS platforms running Repast 2.0 and MASON. In addition, researchers from MITRE Inc., in collaboration with the authors, are porting the model to a multi-processor computing environment using Repast HPC to evaluate the feasibility of building a massive-scale ABM (~10^8 U.S. taxpayers). One of the goals of this exercise will be to investigate how scale influences taxpayer behavior [30, 31].

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Overview, Design Concepts, and Details (ODD) Protocol

for

A Large-Scale Agent-Based Model of

Taxpayer Reporting Compliance

1. Purpose

IRCM is designed to enable tax administrators to explore alternative enforcement strategies (e.g. audit case selection, computerized validation through use of third-party information reporting) for improving the compliance of individual taxpayers.

2. Entities, state variables, and scales

The IRCM has five major types of entities: *Region, Filer, Tax Agency, Preparer*, and *Employer*. A *Region* is an integral unit of geography (e.g. state, county, or city) that is composed of one or more *Zone* entities. *Zones* are non-overlapping areal sub-units located entirely within the *Region* (e.g. postal zip code zones). A *Filer* in IRCM represents an individual tax filer. In the current version of IRCM there are 84,912 filers who reside in the test-bed region. Each filer files a tax return (an instance of the *TaxReturn* class) which, in turn, contains 180 items (elements). A *Preparer* prepares clients' tax returns unless the filer self-prepares. An *Employer* employs filers, except for the self-employed. Filers, preparers, and employers are allocated to zones based on identifiers contained in actual tax return data. A single tax agency (an instance of the *TaxAgency* class) reviews and validates filed tax returns for accuracy against available third-party information documents and audits tax returns. Each simulation time step represents a tax filing year. The number of time steps is a user input.

3. Process overview and scheduling

The main process is tax return filing, which is performed once per time step. A second set of processes involves the actions of the tax agency, which reviews all filed tax returns and selects returns for audit. The tax agency review of tax returns involves comparing the amount reported on each major line item to the amount reported on third-party information documents, if they exist for a given item. Discrepancies are flagged and an Automated Underreporter (AUR) notice is issued if the discrepancy exceeds a user-specified threshold. There are three types of audit selection strategies: Random, Fixed, and Constrained Maximum Yield (CMY). The number of audits to perform (N) is a user input. Under Random selection the tax agency selects N returns at random. Under Fixed selection the tax agency selects a user-specific fixed number of returns in each of 17 non-overlapping audit classes. The CMY selection strategy uses a simple greedy-type algorithm that targets taxpayers in audit classes having the highest average yield (tax). The order in which the returns are filed or processed is unimportant; therefore, scheduling is not a consideration in IRCM.

4. Design concepts

(a) Basic principles

People exhibit heterogeneous reporting behaviors when filing their tax returns. Some appear to behave as rational decision makers, others comply out of a sense of duty or fear, and some pattern their reporting behavior by taking cues from family and friends. In addition to these varying motivational factors, taxpayers have different opportunities for evasion based largely on the source of their income. Finally, taxpayers learn through repeated interactions with other taxpayers, paid preparers, and the tax authority what noncompliance behaviors are more likely to avoid detection. Analytical models in the tradition of Allignham and Sandmo [2] assume taxpayers are independent rational self-interested actors motivated to comply solely due to probability of detection and associated fines. However, empirical evidence from laboratory experiments, field studies, and taxpayer random audits suggests that a variety of non-economic considerations also influence taxpayer reporting decisions. Agent-based models, like IRCM, are capable of incorporating both rational and behavioral motivations in a heterogeneous population of taxpayers.

(b) Emergence

The main emergent feature is a stochastically stable level of compliance (for major line items and total tax) that reflects user-specified assumptions for the level, quality, and effectiveness of tax agency enforcement activities and individuals' behavioral and filing characteristics.

(c) Adaptation

Filers adapt their reporting behavior to the perceived enforcement environment as determined from repeated interactions with the tax agency and (optionally) their neighbors and coworkers.

(d) Objectives

The overall objective for each filer is to achieve a level of tax compliance consistent with their perception of the tax enforcement environment as well as their individual behavioral and filing characteristics.

(e) Learning

Filers may adjust their reporting behavior if they are audited or someone they know (e.g. a neighbor or coworker) is audited. This learning behavior is modeled as a partially observable Markov decision process (POMDP) $\Sigma = (S, A, P, C, O)$, where

- S is a finite set of states $(s \in S)$ (e.g. audited, not audited)
- A is a finite set of actions $(a \in A)$ to perform (e.g. perfect compliance, increase compliance, decrease compliance, no change)
- P is a set of user-supplied probabilities that determine the type of action to take
- C is the cost from transition to state s' from state s with transition probability $P_a(s' \mid s)$
- O is a set of observations ("belief states") with probabilities $P_a(o \mid s)$, for any $a \in A$, $s \in S$ and $o \in O$. $P_a(o \mid s)$ represents the probability of observing o in state s after executing action a

IRCM does not explicitly model costs (C) and belief states (O) but assumes these are implicit in the stochastically determined "choices" made by filers. These elements could be added to the model when better data on taxpayer decision making becomes available. IRCM allows users to provide independent sets of choice probabilities (P) to reflect different degrees of responsiveness by filers to a tax audit of themselves or someone in a reference group (see *Collectives* below).

(f) Prediction

IRCM makes no predictions about future taxpayer behavior but simply models the presumed behavior of taxpayers given certain enforcement conditions.

(g) Sensing

Sensing occurs when filers become aware that someone in either their coworker or neighbor reference groups has been audited. This "sensing" is achieved by a filer polling her reference group members. If a reference group member has been audited, it is assumed that this information is openly communicated to all other reference group members. Lastly, the tax agency can use audits as a sensing mechanism if the CMY selection strategy is used.

(h) Interaction

The main types of interactions in the model that can potentially influence the behavior of individuals include (a) tax agency audits of filers and (b) filers polling members of their reference groups to determine if someone was audited in the previous time period. Implied interactions occur between tax preparers and their clients. However, these preparer-client "interactions" are only implied since they appear as differences in estimated coefficients used to impute misreported amounts for paid prepared and self prepared taxpayers.

(i) Stochasticity

Stochasticity is an integral feature of IRCM. One way the model uses stochasticity is to determine which filers become "stop filers" at each time step. If the stop filer option is activated (the default setting) a uniform random number is drawn and compared to a fixed probability of becoming a stop filer as determined from analyzing filing behavior in the study area. Stop filer probabilities are specific to filing status. Another use of stochasticity is determining which filers are audited at each time step. Audit cases may be selected completely at random or using one of two targeted strategies. The IRCM has 17 pre-determined audit classes used for targeted audits. These audit classes are groups of filers that share certain characteristics. These include: filing status (single, married filing joint/qualified widow(er), head of household, married filing separate, dependent filer), children at home (yes/no), itemized or standard deduction, adjusted gross income (AGI) greater than the median (by filing status), and wage income more than one-half of AGI. Targeted audits may either be fixed in number or use a search algorithm (i.e. Constrained Maximum Yield) that assigns cases to audit classes with the highest average tax yield. A third use of stochasticity involves modeling filers' response to being audited. The user defines a vector of response probabilities (e.g. perfect compliance, increase compliance, decrease compliance, no change) and the model generates a uniform random number to determine which category of response the filer "selects". When the rule-based reporting regime is selected, IRCM uses a stochastic process to assign line item reporting behavior to each taxpayer. The model first determines if a filer is a "deontological" filer meaning that the filer has perfect compliance. If a line item is subject to information reporting and/or withholding IRCM determines how much the filer will report using separate random draws for information reporting and withholding, depending on which conditions apply. Stochasticity is also involved in the process of imputing misreported income and offset amounts. These values are imputed from estimated equations that are fit to empirical cumulative distribution functions (ECDFs). Uniform [0, 1] random numbers are generated and used to select imputed amounts from these equations. Finally, creating reference groups involves stochasticity. Members of a filer's coworker and neighbor reference groups may be structured as either random or "small world" networks. In the former, reference group members are assigned using random selection from a filer's coworkers and neighbors. The process of creating "small world" networks is the same as random except one individual (the "hub") is known to all of the firm's employees or residents of a given zone. The "hub" is determined by random selection.

(j) Collectives

There are two types of filer reference groups: neighbor and coworker. These are determined at the time of instantiation. Both groups assume the same (user specified) fixed size. If the "stop filer" option is activated (the default setting), then reference group stop filers are replaced over time; however, this does not affect group size or member relationships. Preparer networks are a third type of collective that may be optionally specified. At present, preparer networks only become relevant for scenarios that simulate a preparer-based tax scheme.

(k) Observation

IRCM generates output in the form of tables and figures. These can be copied and pasted into other applications for further analysis. The main interface screen also has a “map” of the study region and component zones. Options are provided that allow a user to drill down to view model output for individual preparers and employers by zone. This capability is especially useful for model verification and validation.

5. Initialization

All agents are instantiated when the user selects a data file to read. The order in which agents are instantiated is as follows:

(1) Region and Zones
(2) Employers
(3) Preparers
(4) Filers
(5) Tax Agency

Once these entities have been created and default values assigned the following relationships are added:

(1) Filer + Zone
(2) Filer (client) + Preparer
(3) Filer (employee) + Employer
(4) Preparer + Zone
(5) Employer + Zone

Last, preparer networks and filer reference groups are created (see *Collectives*).

6. Input data

IRCM uses tax return information from the Statistics of Income (SOI) Public Use File (PUF) to describe the filing characteristics of taxpayers in the study region. PUF records are substituted for the tax returns of filers in the study region using statistical matching (performed outside of the model). In addition to the PUF data, filer data includes pseudo-values for the paid preparer taxpayer identification number (TIN), employer identification number (EIN) and zone id as well as a calculated ratio of primary to secondary earnings and an estimate of the number of children living at home under the age of 17. These non-PUF values are derived from filers’ tax returns and are used to preserve key filer relationships that influence reporting behavior and tax calculation. Once the data set is constructed the name of the data file becomes an input parameter to the model. IRCM allows the user to create and save all model parameters used to define a scenario in an xml file. This facilitates the re-creation of scenarios for sensitivity testing and model verification and validation.

7. Submodels

Submodels are provided to analyze alternative behavioral assumptions for paid preparers and employers. The paid preparer submodel enables the user to change the reporting compliance of filers using a paid preparer up or down relative to default levels for all preparers (region) or only for preparers in a specific zone. Networks of preparers (conceptually similar to filer reference groups) can also optionally be created by specifying the network size and the proportion of network members located in the same “home” zone for a given preparer. A fraction of preparers also may be resistant to network influences and an option is available to indicate this as well. The employer submodel permits the user to explore the impact on compliance if some fraction of firms converts their workers from employees to independent contractors (ICs). Conversion of employees to ICs has several advantages for firms such as employers are no longer responsible for making payments of state unemployment tax or withholding of employees’ income tax. In addition, ICs, not firms, become responsible for paying the employers’ share of Social Security and Medicare taxes. The model represents the conversion of employees to ICs by converting wage income to Schedule C income, determining the baseline reporting rate on this income (based on NRP random audit data), and using the tax calculator to determine income tax and employment tax liabilities.