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Research Article

The Effect of Platform Data Quality on Tax Compliance in Digital Economy: A Multiagent Based Simulation

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The expeditious development of the digital economy has posed critical challenges for tax compliance. Recent reforms and technological changes, such as the emergency of platform data sharing, perform as potential instruments to potentially solve the tax compliance issue in the digital economy. This article innovatively combines tax compliance and digital economy taxation and proposes an expected utility theory model and a multiagent simulation model of tax compliance in the context of the digital economy, incorporating an important impact factor—platform data quality. In addition, the discrepancy and applicable conditions of three audit modes have been first compared and analyzed in this research: unconstrained signal audit, constrained random audit, and constrained signal audit. Applying computational experiments, this paper further investigates the effect of platform data quality on tax compliance in the digital economy. The key findings include: (1) the signal role of platform data is affected by three factors—the quality of platform data, the audit intensity and audit rate; (2) the signal role of platform data can be negative in given situations; and (3) the tax compliance rate varies in three different audit modes, which depend on the platform data quality, audit rate, and audit intensity. Based on the findings, this article provides policy recommendations on tax collection and management in digital economy.

1. Introduction

According to the statistics promulgated by the China Academy of Information and Communications Technology, the digital economy scale of the world's 47 major economies have reached \$38.1 trillion in 2021, an increase of 15.5% over 2020. Particularly, the digital economy scale of China has reached \$7.1 trillion, ranking it in second place in the world. With the rapid development and expansion of the digital economy, taxation issues in the digital economy have attracted much attention, both practically and academically. More recently, the Chinese government has encountered challenges in implementing effective tax management in the context of digital economy, which results in a reduced level of tax compliance and substantial tax revenue losses. We approached Cai Chang, the Director of the Centre for Tax Planning and Law at the Central University of Finance and Economics and noticed that the tax revenue losses from consumer-to-consumer (C2C) e-commerce had exceeded ¥100 billion in 2018.

Tax compliance means that taxpayers declare and pay their taxes truthfully; otherwise, it is tax noncompliance. The taxpayers in this paper refer to individuals or corporations that utilize digital platforms to engage in transactions. It is the tax noncompliance of some taxpayers that leads to a large amount of tax revenue losses. Under the digital economy, it is hard for tax authorities to obtain real tax-related data because transactions are characterized by digitization, virtualization, and conceptualization, especially for individuals, who can achieve transactions even without tax registration. Therefore, the information asymmetry between tax authorities and taxpayers in the digital economy is more prominent than that in the traditional economy. In this case, digital economy taxpayers are more likely to evade taxes, including direct tax (income tax) and indirect tax (value-added tax or sales tax). Similar to the previous literature on tax compliance, the model in this article focuses on income tax [1–4].

A high-quality tax-related data is critical in enhancing the tax compliance level and improving the management efficiency. Based on the Golden Tax Project I to IV (this project is launched in 1992, aiming to establish an efficient and widespread taxation system), China's tax authorities, have made great efforts to broaden the horizons of data sharing within financial institutions and government entities [5, 6]. In addition, in the digital economy, both the supply and demand sides have high requirements on the platform's affiliations during the digital transactions. Given this consideration, some scholars indicated that platform data consisting of third-party data which is available to tax authorities is a potential solution to confront the tax compliance challenges applying the platform information report function [7–10]. The platforms related to tax compliance can be subdivided into commodity trading platforms (Taobao, Jingdong, Amazon, etc.), service trading platforms (Didi, Airbnb, etc.), technology trading platforms (Cloud Service, 3D Printing, etc.), and financial asset trading platforms (Alipay, Apple Pay, etc.). They possess a vast trove of data; for example, Taobao's total database capacity has exceeded 100 PB. Many elements of the platform's transaction data can be used for tax compliance management, including trader identity, address, bank account number, date, amount, and quantity.

After scrutinizing existing literature, we identify that most studies on platform information reporting employ qualitative methods, and the research on how the platform data can enhance tax compliance level remains scant. The study by Xiong et al. [9] is one of the few papers that investigated the signal role of platform data in tax compliance in C2C e-commerce by means of multiagent-based simulation (MABS). However, they did not establish an expected utility theory (EUT) model of tax compliance considering platform data quality as the basis of MABS research and only proposed one signal audit mode which is referred to as a constrained signal audit mode in our paper. Motivated by the research gap and practical needs, this paper investigates the influence of platform data quality on tax compliance in the digital economy. Specifically, the research questions are as follows:

(1) What is the effect of platform data quality on tax compliance rates and tax audit rates in the digital economy?

(2) What is the effect of platform data quality on the signal role of platform data in different audit modes?

(3) How can tax authorities effectively apply platform data in tax administration?

Given the above research questions, this study conducts comprehensive computational experimentation research applying EUT and MABS models, focusing on how platform data quality affects tax compliance in the digital economy.

In the EUT model, taxpayers aim to maximize expected utility. Taxpayers want to reduce the level of income declaration to increase utility; however, they must bear the utility loss caused by punishment. Therefore, taxpayers need to choose an optimal level of income declaration after weighing the benefits and losses. As a traditional economic method, the EUT model can mathematically deduce the influence direction of platform data quality, audit probability, and penalty rate on digital economy tax compliance, providing a theoretically basic model to study tax compliance. However, in order to facilitate derivation, the tax compliance problem is simplified, and taxpayers are assumed to be homogeneous and completely rational in the EUT model. In addition, it is difficult to compare and analyze tax compliance under different audit modes through the EUT model, therefore the signal effect of platform data cannot be quantitatively analyzed. While the MABS model can make up for the shortcomings of the EUT model. In reality, the taxpayers have limited rationality because they do not know the actual audit probability and can only estimate it by experience. The heterogeneity of taxpayers is also considered in the MABS model, e.g., risk preference and the differentiation judgment of audit probability. In addition, the impact of the audit mode on tax compliance can be incorporated into the MABS model by setting different audit rules in the simulation program. Taxpayers' social networks and interactions can also be considered in the simulation model [11]. However, the research focuses on the impact of platform data quality on tax compliance in the digital economy; therefore, the interactive imitation behaviors and social networks of taxpayers are not incorporated into the MABS model.

The remainder of this paper is organized as follows. Section 2 provides a literature review and Section 3 develops the EUT model. Section 4 formulates the MABS model. Section 5 expounds the experimental design. Section 6 conducts the experiment with outcomes explanations. Finally, Section 7 presents conclusions and policy recommendations.

2. Literature Review

This paper reviews two streams of related studies: (1) digital economy taxation and (2) tax compliance.

2.1. Digital Economy Taxation. In light of the continuously evolving digital economy, innovative business models are emerging, including online retail, online advertising, sharing economy, cloud computing, live streaming, etc. These new business models of the digital economy are characterized by digitization, virtualization, mobility, and platformization [12–16]. A significant reason for the taxation issues of the digital economy is that the traditional tax system is not suitable for the new business models, mainly including nexus determination rules, taxation of user participation in value creation, data value measurement, and income characterization [12, 13, 17–19]. In addition, the backward tax administration for the digital economy is another reason. Digitization has spurred technological innovations, such as platform economy, e-cash, e-commerce, big data, and blockchain, which can be exploited by taxpayers to increase tax evasion when the tax administration does not keep pace with the development of the digital economy [20].

To solve the taxation issues of the digital economy, on the one side, the traditional tax system should be adapted to the digital age. To this end, OECD/G20 has proposed a two-pillar solution, which is described in the pillar one and pillar two blueprint reports [21, 22]. The former aims to ensure that the taxing right on profits is not exclusively determined by reference to physical presence, while the latter one is designed to ensure that multinational enterprises pay a minimum level of tax regardless of where they are headquartered. On the other side, most transactions between buyers and sellers must go through third-party platforms, making these platforms a crucial source of tax-related data. Therefore, the platform data should be effectively utilized by tax authorities [7–9], and governments must supervise whether platforms are enforcing the law correctly because the enforcement activities may conflict with the platform's own commercial interests [10].

2.2. Tax Compliance. Tax compliance research originated in the 1970s [3], with related theoretical models categorized into three groups based on EUT, game theory, and prospect theory. The EUT model of tax compliance was first constructed by Allingham and Sandmo [1] and modified by Yitzhaki [2]. The model analyzes the influence of policy parameters such as tax rate, audit probability, and penalty rate on tax evasion, which is referred to as the Allingham-Sandmo-Yitzhaki (A-S-Y) model. In subsequent years, numerous scholars incorporated additional tax compliance factors into theoretical models, including labor supply, morality, and social norms, etc., and various directions extending the A-S-Y model were studied [23–26]. Particularly, third-party data were considered in some theoretical models of tax compliance [27, 28].

In the A-S-Y model and its extended variations, the assumption on audit probability can be bifurcated into two forms, namely endogenous and exogenous. However, most models assume audit probability is exogenously given, and few models assume it is endogenously variable [1, 4, 28]. For instance, Allingham and Sandmo [1] scrutinized taxpayers' compliance with exogenous audit probability, as well as examined how taxpayers arrive at decisions when audit probability is established by their reported income level. Kleven et al. [28] assumed audit probability as a function of tax evasion amount, and under the context of third-party information reporting, the shape of the function curve takes an S-shape.

In recent years, some scholars have begun to employ MABS to explore tax compliance, connecting individual taxpayers' compliance decisions with the overall level of social compliance and analyzing the emergent macroproperties from the microproperties [29]. In the MABS models of tax compliance, researchers hypothesize that taxpayers are boundedly rational and do not possess knowledge of the true audit probability. Rather, they estimate audit probabilities dynamically based on experience. In addition, taxpayers exhibit heterogeneity, with distinct taxable incomes, risk preferences, behavioral patterns, and estimations of audit probability [9, 30–33].

2.3. Research Contributions. Compared with existing literature, we make the following three research contributions:

(1) We integrate digital economy taxation research with tax compliance research, utilizing the EUT model and MABS to study tax compliance in the context of the digital economy.

    From the perspective of existing literature on digital economy taxation, scholars have predominantly focused on examining the mismatch between archaic tax regulations and modern business models. These investigations typically explore tax laws and regulations as well as administration frameworks, and offer solutions. The majority of this research comprises qualitative analyses with minimal integration of tax compliance models. There is a dearth of studies on tax compliance within the digital economy from the standpoints of information and taxpayer decision-making.

(2) To provide a theoretical foundation for the MABS model, we establish the EUT model on tax compliance in which platform data quality and endogenous audit probability are considered.

    This paper assumes that the audit probability is a function of the estimated tax evasion amount determined by the tax authority. The estimated tax evasion amount is related to the platform data quality. The higher the quality of platform data is, the more accurate the tax authorities' estimates of the tax evasion by taxpayers. It should be noted that no prior literature has proposed such an assumption. For instance, although Allingham and Sandmo [1] considered a heterogeneous audit probability in their seminal paper, they assumed it is a function of reported income. Furthermore, Kleven et al. [28] and Slemrod [4] assumed that the audit probability was a function of the tax evasion amount, which is not reasonable as the tax authority does not have knowledge of a taxpayer's actual taxable income prior to the audit and, therefore, cannot determine the extent of tax evasion.

(3) To analyze the effects of platform data quality on tax compliance, we consider three audit modes and we analyze their discrepancies and applicable conditions.

The three types of audit modes are unconstrained signal audit (UCSA), constrained random audit (CRA), and constrained signal audit (CSA). Comparatively, the existing MABS researches on tax compliance have only considered CRA and/or CSA, not UCSA. Note that UCSA is a new term for this article.

The distinction between these audit modes resides in the uniformity of audit probability (i.e., the probability of auditing each taxpayer) and the fixed overall audit rate (i.e., the rate of audited taxpayers to all taxpayers) (this article distinguishes between audit probability and audit rate). Within the UCSA mode, tax authorities rely on platform data to estimate taxpayers' tax evasion and subsequently determine the necessity of audits. Consequently, the probability of being audited varies among taxpayers, and the overall audit rate is not constant. The CRA mode factors in the constraint of audit resources, where the overall audit rate remains fixed. In this mode, tax authorities randomly audit all taxpayers, resulting in an equal probability of being audited for each taxpayer, which is equivalent to the overall audit rate. The CSA mode amalgamates the features of the previous two audit modes. The overall audit rate remains constant, but tax authorities prioritize audits based on taxpayers' estimated amount of tax evasion. The priority of audits increases with higher estimated evasion values, leading to differential probabilities of being audited among taxpayers.

3. The EUT Model

3.1. Assumptions. There are five assumptions in this paper.

Assumption 1. The taxable income of digital economy taxpayers (shorted for taxpayers) is y, and taxpayers can choose to declare their income x within the range $[0, y]$.

Assumption 2. If tax authorities engage in cooperative efforts with digital platforms for data sharing, according to which, the tax authorities can evaluate the taxpayer's taxable income ηy, where η represents the quality of the platform data and $0 \leq \eta \leq 1$. The quality of platform data is influenced by two primary factors. First, the extent of platform data sources shared by tax authorities. Given that taxpayers in the digital economy may carry out commercial activities on several platforms concurrently [34, 35], limited cooperation with select platforms would only yield partial tax data, which leads to suboptimal and inadequate platform data for tax assessment. Finally, it results in low precision in tax evaluation. The second factor pertains to the authenticity of platform data. In cases where the platform offers incomplete transaction data or conspires with taxpayers to falsify data, the resultant platform data would also be of poor quality, leading to decreased precision in tax evaluation.

Assumption 3. The audit probability for each taxpayer varies and is contingent upon the estimated tax evasion amount $\tilde{e}$ of the taxpayer, where $\tilde{e} = \eta y - x$, and the audit probability function is $P(\tilde{e})$, where $P(\tilde{e}) = \begin{cases} P(\tilde{e}) & \tilde{e} > 0 \,\&\, P'(\tilde{e}) > 0 \\ 0 & \text{otherwise} \end{cases}$. These conditions indicate that a higher estimated tax evasion amount for a taxpayer correlates with an increased probability of being audited by tax authorities. This assumption is consistent with the tax audit practice of the US discriminant function system and the Chinese tax assessment system [36].

Assumption 4. The tax is proportional to income with rate t. The audit is perfect, implying that any noncompliant behavior by the taxpayer will be detected. Upon such an audit, the taxpayer is liable to pay not only the tax due, $t(y - x)$, but also a penalty amounting to $\pi t(y - x)$, reflecting the extent of tax evasion [1, 2]. Here, π represents the penalty rate.

Assumption 5. The taxpayer is risk-averse, and their utility function is $U(\cdot)$, where $U' > 0$ and $U'' < 0$.

3.2. Model Establishment and Solution. If a taxpayer is audited, his after-tax income is

$$v = y - tx - \pi t(y - x). \tag{1}$$

If a taxpayer is not audited, his after-tax income is

$$w = y - tx. \tag{2}$$

The taxpayer's expected utility is

$$\begin{aligned} EU = {} & P(\eta y - x)U(y - ty - \pi t(y - x)) \\ & + (1 - P(\eta y - x))U(y - tx). \end{aligned} \tag{3}$$

From equations (1)–(3), we obtain Proposition 6.

Proposition 6. *The optimal reported income of taxpayers is x^* and $x^* \leq \eta y$.*

Proofs of all propositions are given in Appendixes A and B.

The economic implication of Proposition 6 is that the lower the quality of platform data, the lower the accuracy of the tax assessment by the tax authorities, and the greater the opportunity for taxpayers to evade taxes.

Proposition 7. *In the case of the interior solution, we have $\partial x^*/\partial \pi > 0$. If $P''(\tilde{e}) \geq 0$, we have $\partial x^*/\partial \eta > 0$; otherwise, the sign of $\partial x^*/\partial \eta$ is ambiguous.*

Regarding tax enforcement, two key factors influencing taxpayer compliance behavior are platform data quality and the penalty rate. Proposition 7 implies that in the case of the interior solution, the optimal reported income of taxpayers rises with the penalty rate. Moreover, if $P''(\tilde{e}) \geq 0$, taxpayers' optimal reported income will definitely increase as platform data quality improves.

4. The MABS Model

4.1. Overall Model Description. This paper explores the tax compliance problem within the framework of the digital economy, incorporating a significant feature of the digital economy known as platformization. In the dual administration model of "government-platform" the tax authority has the capability to utilize the tax-related data offered by the platform to compare it with the taxpayer's declaration data, thus approximating the taxpayer's tax evasion amount. Consequently, the tax authority can distinguish between taxpayers during audits, as evaluated in the preceding EUT model. If the tax authority estimates a greater tax evasion amount, the probability of inspection by the tax authority for the taxpayer will increase.

The agents in the MABS model represent taxpayers and exhibit heterogeneity with regard to their taxable income, assessed taxable income, and judgment of audit probability. Each agent would declare an income to maximize his expected utility. After all the agents report their income, the tax authority selects some agents to audit. To examine the influence of platform data quality on tax compliance, this paper examines three audit modes within the MABS model, namely UCSA, CRA, and CSA, which were previously detailed in the research contribution. Notably, the UCSA mode aligns with the EUT model. Through a comparison of tax compliance rates among the three audit modes under identical audit rates, the conditions and principles relevant to each audit mode can be analyzed.

In the following, we expounded on the main components of the MABS model, including audit probability function, parameters, agent's reporting decision, and program procedure.

4.2. Audit Probability Function. For the UCSA mode, a probability function $P(\widetilde{e})$ must be established based on the aforementioned EUT model. To this end, we assume $P(\widetilde{e})$ is a logistic function, referring to the S-shaped function introduced by Kleven et al. [28]. The probability function $P(\widetilde{e})$ when $\widetilde{e} \geq 0$ is as follows:

$$P(\widetilde{e}) = \frac{1}{1 + Ae^{-k\widetilde{e}}}, \tag{4}$$

where A and k denote two parameters of the logistic function and $A > 0, k > 0$. Given the estimated amount of tax evasion $\widetilde{e}$ by the tax authority, the smaller the value of A and the larger the value of k, the higher the probability $P(\widetilde{e})$ that the taxpayer will be audited, indicating stricter tax audits by the tax authority.

The logistic function is a suitable tool for modeling growth and change processes [37, 38]. This paper employs the logistic function as the audit probability function for two primary reasons. First, the function output is bounded between 0 and 1, which is consistent with the probability range. Second, in reality, when the amount of tax evasion is trivial, the estimated amount of tax evasion by the tax authority may also be inconsequential, resulting in a low likelihood of audit. However, as the amount of tax evasion surpasses a certain critical threshold, the tax authority's attention is likely to be piqued, leading to a rapid escalation in the probability of an audit. The logistic function can effectively depict this real-life scenario.

The first-order and second-order conditions of $P(\widetilde{e})$ are as follows:

$$P'(\widetilde{e}) = kAe^{-k\widetilde{e}}\left(1 + Ae^{-k\widetilde{e}}\right)^{-2}, \tag{5}$$

$$P''(\widetilde{e}) = k^2 Ae^{-k\widetilde{e}}\left(1 + Ae^{-k\widetilde{e}}\right)^{-3}\left(Ae^{-k\widetilde{e}} - 1\right). \tag{6}$$

From equations (5) and (6), it can be seen that $P'(\widetilde{e}) > 0$, and there exists an inflection point $P(\widetilde{e})$ at $\ln A/k$. Furthermore, when $0 \leq \widetilde{e} < \ln A/k$, $P''(\widetilde{e}) > 0$; when $\widetilde{e} > \ln A/k$, $P''(\widetilde{e}) < 0$.

4.3. Model Parameters. The model parameters can be divided into exogenous parameters and agent attribute parameters.

4.3.1. Exogenous Parameters. The number of taxpayers (hereafter referred to as "agents") is denoted by n.

The tax is a proportional tax with a tax rate of t.

The audit mode of the tax authority is represented by m, which can be divided into three types: $m = 1$ represents UCSA; $m = 2$ represents CRA; and $m = 3$ represents CSA.

In the UCSA mode, the audit probability is determined through a joint assessment of the estimated tax evasion amount $\widetilde{e}$ of the agent by the tax authorities and the two critical parameters A and k of the audit probability function. To streamline the experimental process, the model maintains a fixed value of parameter A and regulates the audit probability by manipulating the value of parameter k ($0 < k \leq 1$). To facilitate communication in subsequent discussions, the parameter k is henceforth referred to as the audit intensity parameter. Conversely, in the CRA and CSA modes, the audit rate necessitates setting and is denoted as p, where $0 < p < 1$. The audit is perfect, and if an evading agent is audited, he is liable not only for the taxes owed but also for the incurred additional penalty. The penalty amount is calculated based on the amount of tax evasion, and the penalty rate is represented by π.

Under the circumstances of platform information reporting, the tax authorities can leverage the platform data to assess agents' taxable income. According to the aforementioned EUT model, the evaluated value of an agent's taxable income hinges on the quality of the platform data which is denoted by η, where $0 \leq \eta \leq 1$.

4.3.2. Agent Attribute Parameters. The taxable income of each agent is denoted by y_i, with the assumption that the taxable income follows a uniform distribution between 0 and 100, that is, $y_i \sim U[0, 100]$. It is noteworthy that this distribution is widely utilized in laboratory experiments and computational experiments studies on tax compliance, as highlighted in prior literature [24, 30, 31].

The assessed value of the taxable income for each individual agent is by z_i. To account for the presence of stochasticity, it is posited that z_i follows a uniform distribution over an interval with a 10% fluctuation surrounding the value of ηy_i. This enables the generation of a random assessment of taxable income, z_i, for each agent based on their taxable income, y_i, and the quality of platform data, η.

To focus on the effect of platform data quality on tax compliance within the digital economy, this study postulates that each agent exhibits expected utility maximization as their behavioral type. Moreover, it is assumed that the utility function of each agent can be represented by an exponential utility function [30]. The exponential utility function takes the following form:

$$U_i\left(ATPI_i\right) = 1 - e^{-\lambda_i\left(ATPI_i\right)}, \tag{7}$$

where $ATPI_i$ represents net income after deducting taxes and fines. λ_i is the risk coefficient of the agent, and its value follows a uniform distribution between 0 and 1. A larger risk coefficient indicates a greater risk aversion by the agent.

The reported income of the agent is x_i, and the estimated tax evasion amount of the agent is $\tilde{e}_i = z_i - x_i$. The rationality of the agent is bounded and thus lacks knowledge regarding the true audit probability [4, 30–32]. Instead, they rely on experience to adjust their expected audit probability. Under the UCSA mode, it is assumed that the agent has knowledge of $\tilde{e}_i$ when calculating their expected audit probability, which means that taxpayers know how the tax authority will gauge their tax evasion amount. However, the agent does not possess knowledge or determine the value of the audit intensity parameter k and can only estimate its value, represented by γ_i. In the event that the agent is audited during the preceding period, their assessment of the audit intensity of the tax authority in the current period will rise, leading to an increase in the value of γ_i, such that $\gamma_{i,t} = \gamma_{i,t-1} + \psi_{i,t}$, where $\psi_{i,t}$ is a uniformly distributed random number ranging between 0 and $1 - \gamma_{i,t-1}$. This increase in γ_i prompts the agent to elevate their expected audit probability for the current period. Conversely, if the agent was not audited in the previous period, their judgment of the audit intensity of the tax authority in the current period will decrease, leading to a decline in the value of γ_i, i.e., $\gamma_{i,t} = \delta_{i,t} \cdot \gamma_{i,t-1}$, where $\delta_{i,t}$ is a uniformly distributed random number ranging between 0 and 1. The reduction in γ_i will result in the agent decreasing their expected audit probability for the current period. In the CRA and CSA modes, the agent's expected audit probability is denoted by q_i. In the event that the agent is audited during the preceding period, they will elevate their expected audit probability for the current period, i.e., $q_{i,t} = q_{i,t-1} + \zeta_{i,t}$, where $\zeta_{i,t}$ is a uniformly distributed random number ranging between 0 and $1 - q_{i,t-1}$. Conversely, if the agent was not audited in the previous period, they will reduce their expected audit probability for the current period, i.e., $q_{i,t} = \sigma_{i,t} \cdot q_{i,t-1}$, where $\sigma_{i,t}$ follows a uniformly distributed random number ranging between 0 and 1 [32]. a_i represents whether the agent is audited or not.

The description of all model parameters is summarized in Table 1.

4.4. Taxpayer Agent's Reporting Decision. In the UCSA scenario, the agent's reporting decisions are made based on the previously analyzed EUT model. In this context, the agent's expected utility is calculated via equation (3). Due to the intractability of the expected utility maximization condition expressed in equation (B.1), during the model program's execution, each agent seeks a declared income value, x_i, within their taxable income range $[0, y_i]$, which maximizes the equation (3).

Under the CRA and CSA scenarios, the agent will choose a reporting level that maximizes their expected utility, as analyzed in the A-S-Y model [1, 2]. In this case, the agent's expected utility is

$$\begin{aligned} EU_i\left(y_i, x_i\right) = {} & \left(1 - q_i\right)\left(1 - e^{-\lambda_i\left(y_i - tx_i\right)}\right) \\ & + q_i\left(1 - e^{-\lambda_i\left(y_i - ty_i - \pi t\left(y_i - x_i\right)\right)}\right), \end{aligned} \tag{8}$$

where $y_i - tx_i$ and $y_i - ty_i - \pi t\left(y_i - x_i\right)$ represent the net income of the agent under the circumstances without and with audit, i.e., $ATPI_i$, respectively.

By drawing on the solving process of the A-S-Y model, the condition for the existence of an interior solution that maximizes expected utility can be derived as follows:

$$\frac{1}{1 + \pi e^{\lambda_i(1+\pi)ty_i}} < q_i < \frac{1}{1 + \pi}. \tag{9}$$

If the equation (9) holds, the income declared by the agent can be obtained as follows:

$$x_i = y_i - \frac{\ln\left[\left(1 - q_i\right)/\left(q_i\pi\right)\right]}{\lambda_i t\left(1 + \pi\right)}. \tag{10}$$

If $q_i \geq (1/1 + \pi)$, the taxpayer will report their entire taxable income, while if $q_i \leq (1/1 + \pi e^{\lambda_i(1+\pi)ty_i})$, the taxpayer will report zero taxable income.

4.5. Model Program Procedure. The model program was implemented using NetLogo 6.0.1, encompassing two subprograms, setup and go, as delineated in Figure 1. The program procedure is as follows:

(1) Set various exogenous parameters, such as tax rate, penalty rate, audit mode, audit rate, and platform data quality.

(2) The setup subprogram is implemented, which generates agents and initializes all agent attribute values.

(3) The go subprogram is executed, which comprises two subprograms: taxpayers-report and tax-authority-audit. These correspond to the agent's reporting decision-making process and the tax authority's audit decision-making process, respectively. The taxpayers-report subprogram is executed first, followed by the tax-authority-audit subprogram. Within the taxpayers-report subprogram, agents determine the optimal reported income utilizing the decision mechanism explicated in Section 4.4. Within the tax-authority-audit subprogram, the audit-signal1, audit-random, or audit-signal2 subprogram is selected, corresponding to the three audit modes of UCSA, CRA, and CSA, based on the initially set audit mode. Following the completion of the tax authority's audit, the agent adjusts their expectations regarding the audit probability. The adjustment mechanism is comprehensively outlined in Section 4.3.

Table 1: Description of all parameters in the MABS model.

Type	Notation	Definition	Range
Exogenous parameters	n	Number of agents	Positive integer
	t	Proportional tax rate	(0, 1)
	p	Audit rate	(0, 1)
	π	Penalty rate	$(0, +\infty)$
	m	Audit mode	{1, 2, 3}
	A	Invariant parameter in the audit probability function	$(0, +\infty)$
	k	Variable parameter in the audit probability function, used to control the audit probability of the tax authority, abbreviated as audit intensity parameter	(0, 1]
	η	Quality of platform data	[0, 1]
Agent attribute parameters	y_i	Taxable income of the agent	$U[0, 100]$
	z_i	Assessed taxable income of the agent	$U[0.9\eta y_i, 1.1\eta y_i]$
	λ_i	Risk coefficient of the agent	$U[0, 1]$
	x_i	Declared income of the agent	$[0, y_i]$
	γ_i	Estimated value of parameter k in the audit probability function by the agent	(0, 1]
	q_i	Expected audit probability of the agent	(0, 1)
	a_i	Whether the agent is audited	{true, false}

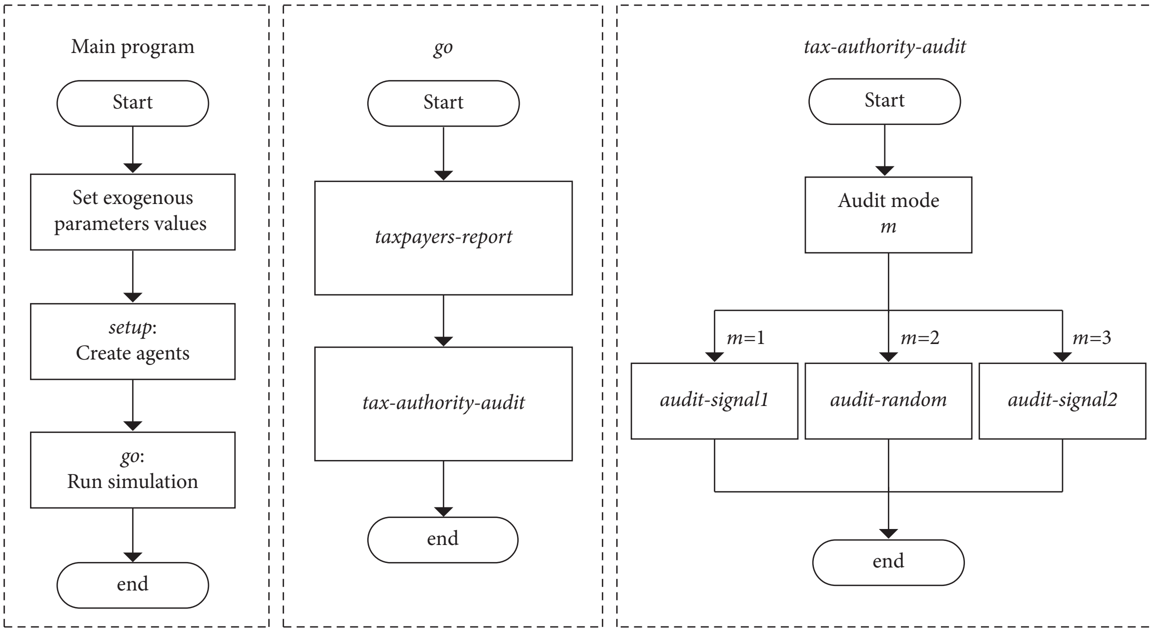

Figure 1: Flowchart of model program execution.

5. Experimental Design

5.1. Experimental Process. The entire experimental process includes the following five steps:

Step 1. We set exogenous parameters. As the primary objective of this study concerns the examination of the influence of platform data quality on tax compliance in the digital economy, certain exogenous parameters, including the tax rate and penalty rate, were held constant throughout the experiment. The analysis of this issue entailed varying the values of other exogenous parameters such as the platform data quality, audit intensity, and audit rate.

Step 2. By setting the audit mode to UCSA under the condition of the fixed audit intensity parameter, this study aims to continuously adjust the platform data quality, perform experiments to obtain experimental data on tax compliance rate and audit rate under different platform data qualities, and then analyze the platform data quality on tax compliance rate and audit rate in the UCSA mode. The program is executed 50 times for each set of parameters, and 50 experiments are conducted under the same set of parameters. The tax compliance rate and audit rate are calculated using the formulas $\sum_{i=1}^{n} x_i / \sum_{i=1}^{n} y_i$ and $\sum_{i=1}^{i=n} 1_{[a_i]}/n$, respectively, where the function $1_{[a_i]}$ represents: when the value of a_i is true, the function value is 1; otherwise, the function value is 0. Since the tax compliance system reaches an equilibrium state after 10 periods of program running in each experiment, the tax compliance rate and audit rate of the last 10 periods of each experiment are averaged to obtain the tax compliance rate and audit rate of the experiment. To reduce the randomness of the results of a single experiment, the average tax compliance rate and audit rate of 50 experiments are used as the tax compliance rate and audit rate of the parameter set, and the same methodology is followed for subsequent experiments.

Step 3. We analyze the influence of platform data quality on the effect of platform data signals in the UCSA mode. The size of the platform data signal effect under the UCSA mode can be measured by calculating the increase in tax compliance rate relative to the CRA mode under the same audit rate [9]. The strength of the platform data signal effect increases with a larger increase in tax compliance rates. Therefore, to conduct this experiment, the audit mode is set to the CRA, and the audit rate is determined based on the experimental results of the UCSA mode.

Step 4. We analyze the influence of platform data quality on the effect of platform data signals in the CSA mode. The experimental process is similar to step 3.

Step 5. We compare and analyze the tax compliance rates under three audit modes to study the principles of audit mode selection for tax authorities.

5.2. Exogenous Parameter Setting. In all experiments, the number of agents, n, is set to 900.

Regarding the tax rate t, in accordance with the Chinese Enterprise Income Tax Law and pertinent tax incentive policies, the fundamental tax rate for corporate income tax stands at 25%. Small and microprofit enterprises are subject to a reduced tax rate of 20%, whereas key high-tech enterprises that necessitate considerable government support are subject to a reduced tax rate of 15%. Key software and integrated circuit design enterprises, on the other hand, are subject to a tax rate of 10%.

Consequently, the tax rate t may be established at 10%, 15%, 20%, or 25%. For determining the audit rate p, guidance can be sought from the audit documents of the Chinese tax authorities. The Chinese tax authorities carry out categorized audits on taxpayers, with a yearly random audit rate of around 20% for key taxpayers, a maximum yearly random audit rate of 3% for nonkey taxpayers, and a maximum yearly random audit rate of 1% for non-corporate taxpayers. Therefore, the audit rate should be set within the range of 0% to 20%. With regard to the penalty rate π, according to the provisions of the Chinese tax law, its range fluctuates between 0.5 and 5.

The values of two parameters, A and k, embedded in the audit probability function, bear a significant influence on the audit intensity of the tax authorities. When the value of A is smaller and the value of k is larger, the tax authorities' audit becomes stricter, and the audit intensity strengthens. As no empirical research exists on the values of A and k, this study adopts a fixed value of parameter A and adjusts the value of parameter k within the range of $(0, 1]$ to regulate the audit intensity of the tax authorities. However, it is crucial to meticulously deliberate the value of parameter A as an excessively small value results in an overall high audit rate, and vice versa. By conducting numerical simulations of the logistic function for the audit probability and consulting the classified audit rate of the Chinese tax authorities, this study proposes setting the value of A to 100, which appears more rational.

In the ensuing experiments, the tax rate, t, is uniformly established at 20%, and the penalty rate, π, is also uniformly fixed at 2. In different experiments, various parameters such as the audit mode m, platform data quality η, audit intensity parameter k, and audit rate p are modified in line with the specific experimental objectives. The experimental outcomes demonstrate that altering the tax rate and penalty rate has no bearing on the conclusions presented in this paper.

The value of all the exogenous parameters in the simulation experiments is shown in Table 2.

Table 2: Value of exogenous parameters in the simulation experiments.

Notation	Value
n	900
t	20%
p	{1%, 3%, 5%, 10%, 15%, 20%}
π	2
m	{1, 2, 3}
A	100
k	{0.05, 0.1, 0.15, 0.2}
η	{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1}

6. Experimental Results

6.1. The Effect of Platform Data Quality on the Tax Compliance Rate and Audit Rate in the UCSA Mode. We establish the audit mode as UCSA. Subsequently, with a fixed audit intensity parameter k, modify the value of platform data quality η to obtain experimental data on tax compliance rates and audit rates under various platform data quality levels. Throughout the experiment, k values are set to 0.05, 0.1, 0.15, and 0.2. (during the experiment, it was found that if the value of the audit intensity parameter is greater than 0.2, when the platform data quality is high, the audit ratio will significantly exceed 20%, which is not consistent with reality. Therefore, this article only discusses cases where the value is within 0.2), while η values are assigned as 0.1 to 1 with a 0.1 step. The experimental results concerning tax compliance rates and audit rates at varying k and η are presented in Figures 2(a)–2(d).

From Figures 2(a)–2(d), it can be observed that

(1) When the audit intensity remains constant, the tax compliance rate is observed to increase with improvements in platform data quality. According to the EUT model, this result is only valid under the assumption that the second derivative of the audit probability function, denoted as $P''(\widetilde{e})$, is greater than or equal to 0. Despite the fact that the condition $P''(\widetilde{e}) \geq 0$ is not always satisfied for the logistics form of the audit probability function, computational experimental results have shown that the conclusion still holds true.

(2) Synoptically, the observed increase in tax compliance rate associated with improving platform data quality exhibits a continuous decline, i.e., the tax compliance rate curve is concave, which implies that enhancing platform data quality can boost tax compliance rate, while its marginal effect progressively diminishes. This finding is different from that of Xiong et al. [9], who only consider one signal audit mode—CSA. According to their research, the compliance rate rises as platform data quality improves. The parameter of platform data quality is not induced in the model of Xiong et al. [9], but they considered the correlation degree between platform data and taxpayers' taxable income. It can be understood that the stronger the correlation, the higher the platform data quality, and its cure is convex.

(3) The audit rate rises as platform data quality improves, and the rate of increase accelerates over time; namely, the audit rate curve is convex.

(4) Generally speaking, the ratio of audit rate change to tax compliance rate change exhibits a continuous increase with the enhancement of platform data quality. This suggests that while improving platform data quality can enhance tax compliance rates, the tax authority incurs higher and higher audit costs for the same increase in tax compliance rates.

6.2. The Impact of Platform Data Quality on the Signal Effect of Platform Data in the UCSA Mode. Drawing on the experimental design, the audit mode is switched to CRA, while the audit rate p is determined based on the experimental findings reported in Section 6.1, where we explore diverse combinations of audit intensity and platform data quality in the UCSA mode. This setup enables the derivation of tax

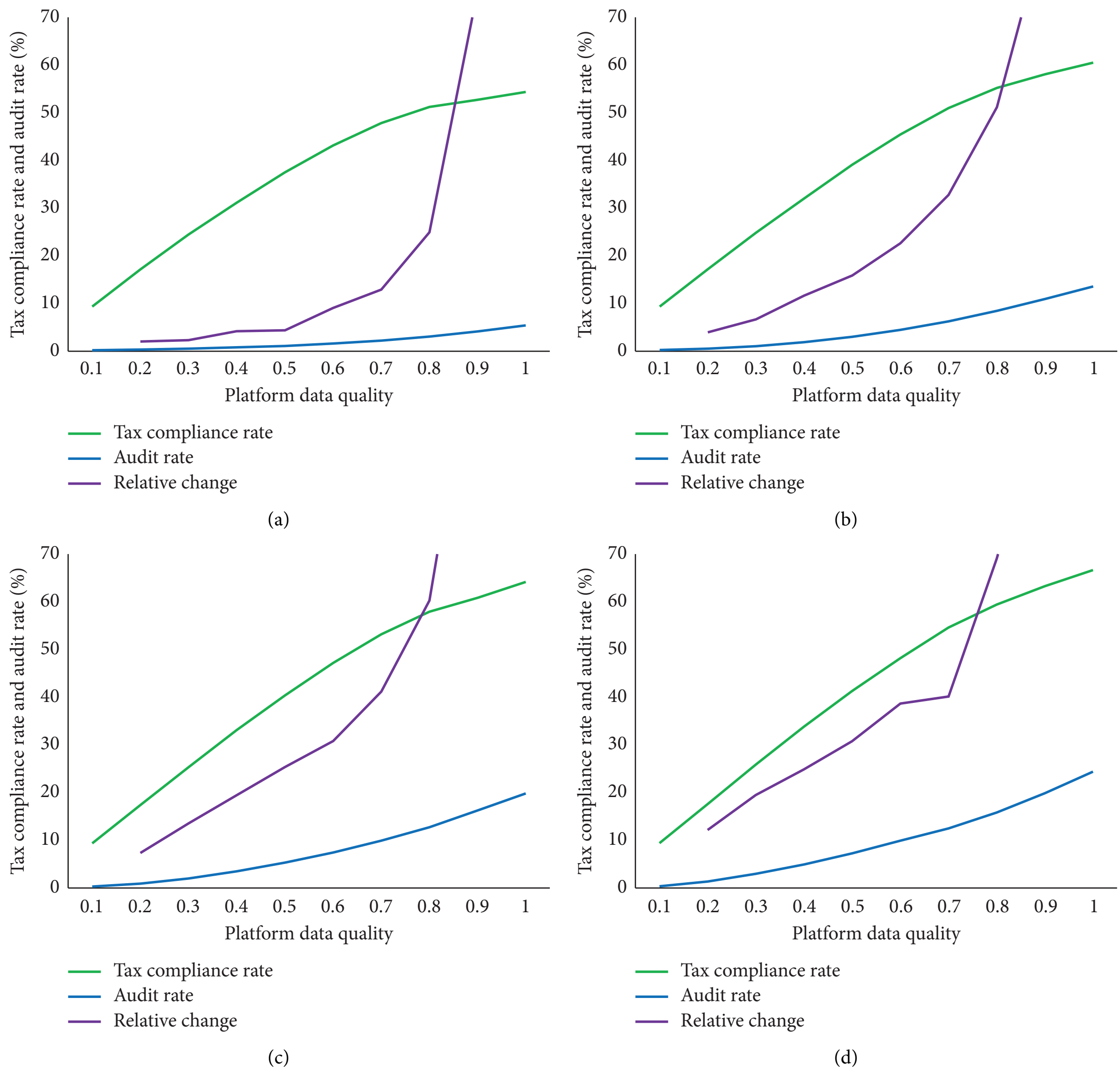

Figure 2: Curves of tax compliance/audit rate vs. the change of platform data quality in the UCSA mode. (a) $k = 0.05$, (b) $k = 0.1$, (c) $k = 0.15$, (d) $k = 0.2$. Note that: Relative change equals to change of audit rate/change of tax compliance rate.

compliance rates in the CRA mode under equivalent audit rate conditions, along with the quantification of the signal effect emanating from the platform data.

The experimental results concerning the signal effect of platform data in UCSA mode at varying k and η are presented in Figure 3.

From Figure 3, it can be observed that

(1) In the UCSA mode, if the tax authority maintains a constant level of audit intensity, the platform data quality improvement results in a gradual increase and subsequent decrease in the signal effect of platform data. Although the signal effect of platform data continues to decrease with an increase in η value when $\eta \geq 0.1$ for $k = 0.2$, adjusting the η value for experiments within the range of (0, 0.1) reveals that the signal effect of platform data still first increases and then gradually decreases. Due to space limitations, relevant data are not presented. Therefore, for a given audit intensity parameter k, there exists a critical value η_c. Specifically, the signal effect of platform data increases with the platform data quality η when $\eta \leq \eta_c$, and decreases with η when $\eta > \eta_c$. It is noteworthy that the experimental findings indicate that the critical value η_c decreases as the audit intensity increases.

(2) When the audit intensity is strong, such as $k = 0.15, 0.2$, the signal effect of platform data may be negative with improvement of the platform data quality. This experimental finding of the negative signal effect of platform data is paradoxical. It suggests that the tax compliance rate is lower under the UCSA mode than under the CRA mode, and the use of platform data for taxation purposes may actually reduce the tax compliance rate.

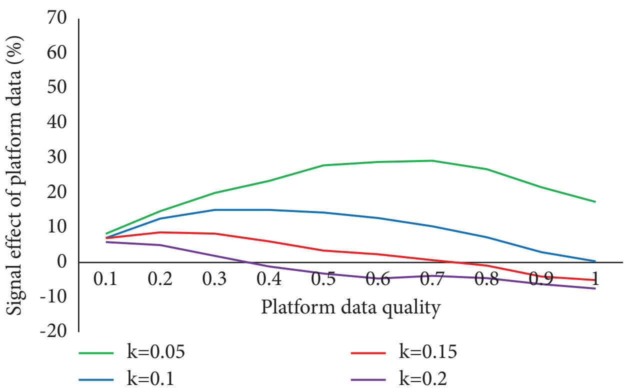

FIGURE 3: Curves of platform data signal effect vs. the change of platform data quality in the UCSA mode.

(3) Augmenting audit intensity leads to a consistent decline in the signal effect of platform data, assuming the platform data quality remains constant.

The experimental results above can be explained as follows. In the UCSA mode, a low quality of platform data generates a low audit rate. Further, the tax compliance rate under the CRA mode with the homologous audit rate is also low, and it increases indistinctively as the platform data quality improves. However, the tax compliance rate under the UCSA mode climbs significantly with the elevation of the platform data quality, leading to the gradual enhancement of the signal effect of platform data. As the quality of platform data continues to improve to a higher level, the audit rate under the UCSA mode rapidly increases, causing a speedy growth in the tax compliance rate under the CRA mode with the homologous audit rate. However, the previous analysis indicates that the increase in tax compliance rate under the UCSA mode decreases as the platform data quality improves, leading to the gradual attenuation of the signal effect of platform data. When the audit intensity parameter k is high, with the improvement of platform data quality, the tax compliance rate under the CRA mode increases too fast, even exceeding that identified under the USCA mode, resulting in a negative signal effect on platform data.

Furthermore, for the same improvement in platform data quality, a larger audit intensity parameter k results in a greater increase in audit rate under the UCSA mode and a corresponding greater increase in tax compliance rate under the CRA mode. This causes the signal effect of platform data to shift from an increasing trend to a decreasing trend more quickly with the improvement of platform data quality. In other words, the critical value η_c decreases with the increase in the audit intensity parameter k. This also leads to a gradual weakening of the signal effect of platform data under the same quality as the audit intensity is strengthened.

6.3. The Impact of Platform Data Quality on the Platform Data Signal Effect in the CSA Mode. First, the value of the audit rate p is set, and the audit mode is designated as CRA for conducting experiments, obtaining the tax compliance rate under this audit rate. Subsequently, the audit mode is switched to CSA, and experiments are carried out with varying platform data quality η while maintaining a constant audit rate, determining the tax compliance rate under different values of quality of platform data. Ultimately, by comparing the tax compliance rate differences between the two audit modes, the signal effect of platform data in the CSA mode can be calculated. During experimentation, p values are set at 1%, 3%, 5%, 10%, 15%, and 20%, while η values range from 0.1 to 1 in increments of 0.1.

The signal effects of platform data at different η and p values in the CSA mode are shown in Figure 4.

From Figure 4, it can be observed that

(1) When the audit rate is low (for example, $p = 1\%$), the signal effect of platform data under the CSA mode is sufficiently low and exhibits little change with the improvement of platform data quality, thereby presenting an insignificant trend of enhancement. However, in cases where the audit rate is relatively high ($p \geq 5\%$), the signal effect of platform data under the CSA mode increases gradually with the improvement of platform data quality. This conclusion is in line with the findings of Xiong et al. [9]. The underlying reason for this phenomenon is that under the CSA mode, the tax authorities choose a subset of agents with the highest discrepancy between the assessed taxable income and the declared income as audit targets, and the quantity of audits is dependent on the audit rate. When the audit rate is lower, the tax authorities select fewer audit targets based on platform data, leading to a reduced number of identified tax evasion agents and consequently resulting in a weaker effect of platform data signals.

(2) Considering a fixed platform data quality, the signal effect of platform data under the CSA mode generally exhibits a first gradual increase followed by a gradual decrease with an increase in the audit rate. Only in instances where platform data quality is low ($\eta \leq 0.3$), does the signal effect of platform data increase again when the audit rate is elevated from 15% to 20%. The experimental results can be explained as follows: When the audit rate is extremely low, the signal effect of platform data gradually increases due to the tax authorities' identification of a greater number of tax evasion agents based on platform data. However, when the audit rate is relatively high, the tax compliance rate under the CRA mode experiences a significant increase. Consequently, if the audit rate continues to rise, it becomes increasingly challenging for the increase in tax compliance rate under the CSA mode relative to that under the CRA mode, which implies a gradual weakening of the signal effect of platform data.

(3) In a scenario where the platform data quality is exceedingly low and the audit rate is high, the signal effect of the platform data is found to be negative, showing a fascinating experiment result. The

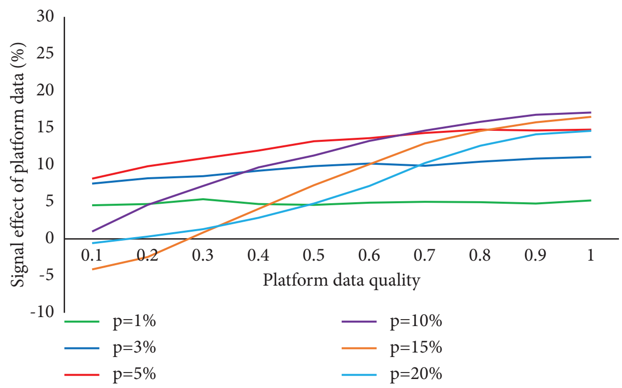

FIGURE 4: Curves of platform data signal effect vs. the change of platform data quality in the CSA mode.

outcomes suggest that under such circumstances, it may be more beneficial for the tax authority to refrain from utilizing platform data, given that the tax compliance rate in the CSA mode is lower than that observed in the CRA mode. This experimental result can be explained by the fact that the extremely low quality of platform data leads to an underestimation of taxable income for high-income agents by the tax authority. Consequently, despite high-income agents engaging in considerable tax evasion, many of them will not undergo inspections due to the tax authority's low estimation of their evasion amounts. This results in a relatively low compliance level among high-income agents. Although the audit rate is high, inspections mainly target low-income agents. As a result, even though low-income agents exhibit a higher level of compliance, the overall tax compliance rate is lowered by the low compliance level of high-income agents. In such a scenario, conducting random inspections of all agents can enhance compliance among high-income agents and improve the overall tax compliance rate.

6.4. Comparison of Tax Compliance Rates under Three Audit Modes and the Selection of Audit Mode by Tax Authorities. The preceding analysis highlights variations in tax compliance rates across three distinct audit modes. In some instances, the tax compliance rate in the signal audit mode that employs platform data can be lower compared to the random audit mode that does not utilize such data. Hence, this section aims to compare and analyze tax compliance rates across the three audit modes, while also exploring how tax authorities should select appropriate audit modes. To this end, this section presents additional experiments supplementing those in Section 6.2, incorporating the CSA mode that operates under the same conditions of audit rate and platform data quality. The findings of these experiments are presented in Figures 5(a)–5(d).

From Figures 5(a)–5(d), it can be observed that

(1) The tax compliance rate ascertained under the CSA mode consistently surpasses that identified under the CRA mode. The converse scenario explicated in Section 6.3 does not manifest. This outcome is attributable to the fact that, in the aforementioned experiments, when the data quality of the platform is exceedingly poor, the audit rate is correspondingly low. Hence, the eventuality of encountering both the low quality of platform data and a high audit rate does not occur.

(2) When the tax authority's audit intensity is low (e.g., with an audit intensity parameter k of 0.05), the tax compliance rate ascertained under the UCSA mode invariably exceeds that determined under the CSA mode. However, in instances where the tax authority's audit intensity is high (e.g., $k = 0.1, 0.15, 0.2$), and the quality of platform data is low, the tax compliance rate identified under the UCSA mode remains greater than that established under the CSA mode. Nevertheless, as the quality of platform data ameliorates, a reversal in the aforementioned scenario takes place. For a higher k value, there should be a critical value η_c, where the tax compliance rate under the UCSA mode is higher than that under the CSA mode when $\eta \leq \eta_c$, and vice versa when $\eta > \eta_c$. Notably, the critical value η_c decreases with an elevation in the audit intensity parameter k value, as evidenced in the experimental findings.

(3) If the level of audit intensity is low (e.g., $k = 0.05, 0.1$), the tax compliance rate when subject to an UCSA mode is consistently higher than that observed when exposed to a CRA mode. In contrast, when the tax authority's audit intensity is high (e.g., $k = 0.15, 0.2$), the tax compliance rate under the UCSA mode is superior to that under the CRA mode only if the platform data quality is low. However, if the quality of the platform data improves, the opposite effect will be observed. The underlying rationale for this experimental outcome has been explicated in Section 6.2.

In light of the preceding findings, including those presented in Section 6.2 (which reveals a negative signal effect of platform data when the tax authority's audit intensity and platform data quality are high under the UCSA mode) and Section 6.3 (which indicates a negative signal effect of platform data under the CSA mode when the platform data quality is extremely low and the audit rate is high), it can be deduced that platform data sharing is a viable strategy for improving the tax compliance rate of the digital economy. Nonetheless, when tax authorities utilize platform data for digital tax administration, it is imperative that they select an

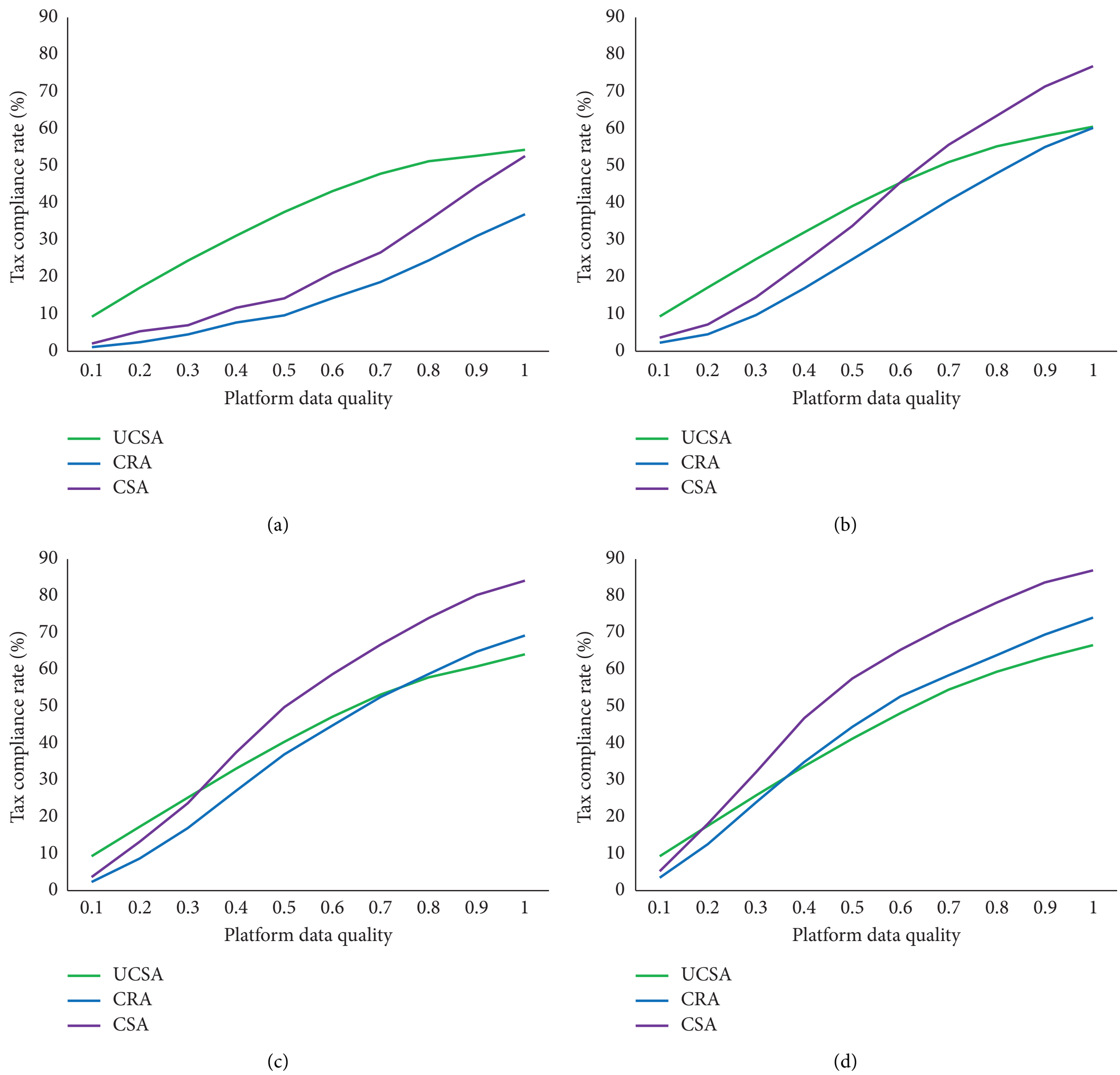

Figure 5: Curves of tax compliance rate vs. the change of platform data quality under three audit modes. (a) $k = 0.05$. (b) $k = 0.1$, (c) $k = 0.15$, (d) $k = 0.2$.

appropriate signal audit mode. In instances where the platform data quality is low, the tax authority should opt for the UCSA mode, but with a reasonable and not excessively high audit intensity. When the platform data quality is high, the tax authority may utilize the UCSA mode, but with a lower audit intensity. In such a scenario, if the tax authority seeks to further improve the tax compliance rate, it should not solely rely on increasing the audit intensity. Instead, it should adjust the audit mode to the CSA mode, while ensuring that the audit rate is not excessively low.

7. Conclusion

This paper employs an expected utility theory to investigate tax compliance issues in the digital economy context, which incorporates platform data quality in the analytical framework. A multiagent simulation model consisting of three audit modes, namely, UCSA, CRA, and CSA is developed to analyze the influence of platform data quality on tax compliance. We further conduct computational experiments, from which, the key findings are as follows:

(1) In the UCSA mode, given an unchanged intensity of tax audit, both the tax compliance rate and audit rate increase with the improvement of platform data quality. Also, the change ratio in audit rate and tax compliance rate performs a continuous rise.

(2) In the UCSA mode, when the intensity of the tax audit keeps constant, the signal effect of platform data presents an intricate curve that first increases and then decreases with the improvement of platform data quality, and in some cases, can drop to be negative. Moreover, under identical platform data quality conditions, the signal effect of platform data

continuously diminishes as the intensity of the tax audit amplifies.

(3) With respect to the CSA mode, when the audit rate is low, the signal effect of platform data is weak. However, when the audit rate is relatively high, the signal effect of platform data augments with the improvement of platform data quality. With a constant platform data quality, when the audit rate increases, the signal effect of platform data can experience a rising trend followed by a declining trend. Also, when the platform data quality is low and the audit rate is high, the signal effect of the platform data is negative.

(4) The tax compliance rates of three distinct audit modes exhibit variation depending on the factors such as audit rate, quality of platform data, and audit intensity. Particularly, when the audit rate is low, the tax compliance rate is higher under the CSA mode than which is under the CRA mode. Whereas when the audit rate is high and the platform data quality is substantially low, contrary results are indicated.

(5) Where the tax audit intensity is low, the tax compliance rate under the UCSA mode is always higher than that under the CSA mode. When the tax audit intensity is high and the platform data quality is low, the tax compliance rate under the UCSA mode is higher than that under the CSA mode. However, with an improvement in the quality of platform data, the outcomes are contrary.

(6) When the tax audit intensity is low, the tax compliance rate under the UCSA mode is always higher than that under the CRA mode. Contrarily, when the tax audit intensity is high and the platform data quality is low, the tax compliance rate under the UCSA mode surpasses that under the CRA mode. However, with an improvement in the quality of platform data, the situation is reversed.

In terms of the research findings, this paper provides three political implications for the tax management in the digital economy as follows:

(1) Tax authorities can promote the implementation of data sharing with prominent digital economy platforms. There is a need for governments to enhance the relevant legal framework for platforms underpinning the platform data sharing. In addition, the government can establish a regulatory department aiming to supervise the platform data and prevent any potential collusion between platforms and taxpayers to furnish deficient or spurious data.

(2) Tax authorities are advised to adopt an appropriate audit approach in accordance with the quality of the platform data. During the initial stage, when the data shared by platforms is incomplete and of low quality, tax authorities can choose the UCSA mode and abstain from employing excessive audit intensity. As the quality of platform data improves gradually, tax authorities may continue to utilize the UCSA mode; however, the audit intensity needs to be kept at a lower level. In such circumstances, if tax authorities aim to enhance tax compliance, they need to select the CSA mode and ensure that the audit rate is not marginal.

(3) Given that a substantial number of individuals are participating in diverse commercial activities through platforms, there is a significant surge in the number of taxpayers. Hence, to maintain a satisfactory audit rate, tax authorities need to reinforce the incorporation of artificial intelligence technology into the audit system.

A number of potential avenues for future research can be explored. First, various social networks can be incorporated into the multiagent simulation model, and thereby the influence of platform data on the conformity effect of taxpayer compliance behaviors can be further investigated. Second, relevant empirical studies can be conducted by collaborating with tax authorities in the future. Third, the limitations in our model can be refined and improved accordingly.

Appendix

A. Proof of Proposition 6

From Assumption 3, if $\tilde{e} \leq 0$, then $P(\tilde{e}) = 0$. Therefore, from equation (3), if a taxpayer reports an income $x = \eta y$, then the expected utility of the taxpayer is equal to $U(y - \eta y)$. If the taxpayer reports an income $x > \eta y$, then his expected utility is less than $U(y - \eta y)$. Therefore, the optimal reported income of taxpayers cannot exceed ηy.

B. Proof of Proposition 7

The first-order condition for the interior maximum of the taxpayer's expected utility is

$$\begin{aligned} &\pi t P(\tilde{e})U'(v) - P'(\tilde{e})U(v) - t(1 - P(\tilde{e}))U'(w) \\ &\quad + P'(\tilde{e})U(w) = 0. \end{aligned} \tag{B.1}$$

If an interior solution exists, it must satisfy the following conditions simultaneously: $\partial EU/\partial x|_{x=0} > 0$ and $\partial EU/\partial x|_{x=\eta y} < 0$, which means $t[\pi P(\eta y)U'(y - (1 + \pi)ty) - (1 - P(\eta y))U'(y)] + P'(\eta y)[U(y) - U(y - (1 + \pi)ty)] > 0$ and $P'(0)[U((1 - \eta t)y) - U((1 - t - \pi t(1 - \eta))y)] - tU'((1 - \eta t)y) < 0$.

The second-order condition for maximizing taxpayer's expected utility is

$$\Omega = \pi t\left[\pi t P(\tilde{e})U''(v) - 2P'(\tilde{e})U'(v)\right] - t\left[2P'(\tilde{e})U'(w) - t(1 - P(\tilde{e}))U''(w)\right] + P''(\tilde{e})[U(v) - U(w)]. \tag{B.2}$$

Equation (B.2) consists of three terms, with the first and second terms being negative, and the sign of the third term contingent upon $P''(\tilde{e})$. Should $P''(\tilde{e}) \geq 0$, $\Omega < 0$ can be determined, thus satisfying the second-order condition. On the other hand, $P''(\tilde{e}) < 0$, it is impossible to determine whether the second-order condition is satisfied or not.

The comparative static analysis is presented as follows:

$$\frac{\partial x^*}{\partial \eta} = \frac{P'(\tilde{e})ty\left[\pi U'(v) + U'(w)\right] + P''(\tilde{e})y[U(w) - U(v)]}{-\Omega}, \tag{B.3}$$

$$\frac{\partial x^*}{\partial \pi} = \frac{P(\tilde{e})t\left[U'(v) - \pi t(y - x)U''(v)\right] + P'(\tilde{e})t(y - x)U'(v)}{-\Omega}. \tag{B.4}$$

From Assumption 3, the authors have $P'(\tilde{e}) > 0$. From Assumption 5, the authors have $U'(v) > 0$, $U'(w) > 0$, $U''(v) < 0$, and $U(w) > U(v)$. If an interior solution exits, the authors have $\Omega < 0$. Therefore, $\partial x^*/\partial \pi > 0$. In addition, if $P''(\tilde{e}) \geq 0$, the authors have $\partial x^*/\partial \eta > 0$; otherwise, the authors are unable to determine its sign.

Data Availability

No data were used to support the findings of this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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