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Does machine interaction encourage tax compliance?

An experimental study

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Abstract:
This study aims to experimentally investigate whether or not there is a difference in tax compliance behavior if the tax auditor is a human (participant) or a computer, assuming a game-theory-based situation. In recent years, with the rapid development of computers and information technology, artificial intelligence and other machines have become part of our lives in various fields. Recent research suggests that people make important distinctions between machines and humans. Our experimental results show that a taxpayer's reporting behavior is less tax compliant for the computer compared to the human auditor condition. Further, focusing on the individual characteristics, men evade tax payments more aggressively than women under the computer auditor condition, and participants with prosocial tendencies are more likely to engage in tax compliance when the tax auditor is a human. Our study sheds light on policymaking for tax compliance in the digital age.

Keywords: tax compliance game; experiment; computer auditor; gender; prosociality.

1. INTRODUCTION

In recent years, with the rapid development of computers and information technology, artificial intelligence (AI) and other machines have become part of our lives in various fields. In the accounting world, this development of machines (including AI) has considerably impacted auditing. Currently, the impact of AI in auditing is particularly pronounced in the area of data acquisition such as data extraction, comparison, and verification (Brennan, Baccala, and Flynn 2017). This means that AI-enabled technology allows human auditors to locate relevant information, extract it from documents, and devote more time to areas that require higher-level decisions.

A similar story applies to the world of tax audits. According to a World Street Journal article, governments are increasingly relying on machine learning and data analytics to analyze a trove of data as they seek to detect tax evasion, respond to taxpayers' questions, and increase efficiency.[1] The Internal Revenue Service (IRS) is designing machine-built graphs to plot relationships between taxpayers in transactions, giving auditors a new tool to analyze transactions and detect tax evasion. The IRS uses AI to study the notes that their employees take when answering questions from taxpayers, testing which combination of formal notice and contact information is most likely to induce a taxpayer who owes money to make a payment. While AI tax audits can be helpful, they create other problems. A real risk exists if the algorithm for selecting audits inadvertently causes discrimination against certain taxpayers based on race or location. Heavy reliance on technology could also make an already seemingly detached agency even more impersonal, potentially missing an opportunity to correct the misunderstandings of taxpayers who believe the government is out to get them and alienating those who want to deal directly with IRS employees. University of California, Irvine law professor Victor Fleischer said, "The tools are only going to be as good as the people employing

[1] https://www.wsj.com/articles/ai-comes-to-the-tax-code-11582713000

them.” In other words, while people can recognize the existence of a problem, AI and other algorithm-based technology cannot solve unknown problems. Thus, an even greater danger of heavy reliance on such technology lies in overpassing some important, newly emerging issues. Meanwhile, tax preparers and accounting firms have been using similar tools to minimize their tax bills. All four of the big four accounting firms have experts that provide advice to their clients by taking advantage of AI.

This study aims to experimentally investigate whether or not there is a difference in tax compliance behavior if the tax auditor is a human (participant) or a computer, by building on the assumption of a situation based on game theory. In game theory, it is important to examine how one player’s belief concerning the other player affects the first player’s behavior. Although there have been many empirical studies focusing on tax audit rules, there is still room for research concerning taxpayers’ compliance behavior based on their belief regarding the tax auditor.

Despite having the ability to treat machines like social actors (e.g., Rahwan et al. 2020; Traeger et al. 2020),[2] recent research suggests that people still make important distinctions between machines and humans. Some examples of such research include a human aversion to algorithms (Castelo et al. 2019; Commerford et al. 2021; Dietvorst et al. 2018; Ishowo-Oloko et al. 2019; March 2021) and the diffusion of responsibility between humans and machines (Gogoll and Uhl 2018; Kirchkamp and Strobel 2019; Kipp, Curtis and Li 2020). Specifically, the above

[2] Some studies find that people treat computers in much the same way they treat people. Katagiri et al. (2001) show that people apply social norms from their own culture to a computer. Reeves and Nass (2003) find that people are as polite to computers as they are to humans in laboratory experiments. Nass et al. (1994) demonstrate that people seem to use social rules in addressing computer behavior. Nass and Moon (2000) observe that people ascribe human-like attributes to computers. In a laboratory experiment by Nass et al. (1996), in which participants are told to be interdependent with a computer affiliate, the computer is perceived just like a human teammate. Moon and Nass (1998) even observe that humans tend to blame a computer for failure and take the credit for success when they feel dissimilar to it while blaming themselves for failure and crediting the computer for success when they feel similar to it. Kirchkamp and Strobel (2019) use a modified dictator game with two joint decision makers: either two humans or one human and one machine, and find no treatment effect on perceived responsibility or guilt. Other studies find that computers are held at least partially responsible for their actions. Friedman (1995) reports in an interview on computer agency and moral responsibility for computer errors that 83% of the computer science major students attribute aspects of agency such as decision-making and/or intention to the computer, 21% of the students even held the computer morally responsible for wrongdoing. Moon (2003) shows that the self-serving tendency for the attribution of responsibility to a computer in a purchase decision experiment mitigates when the participants have a history of intimate self-disclosure with a computer. In short, participants’ willingness to assign more responsibility to a computer for a positive outcome and less responsibility to the computer in a negative outcome increases, when the participants share some private information with the computer before the computer-aided purchase decision.

evidence reveals that people can reach a variety of decisions and show different brain activation patterns to machines in the same decision-making tasks for the same financial incentives. For example, Gallagher, Anthony, Roepstorff, and Frith (2002) show activation of the medial prefrontal cortex, a brain region previously implicated in mentalizing (reasoning about an opponent's beliefs, desires, and intentions), when people play rock-paper-scissors with humans, but not when they play with machines that follow predefined algorithms. In another study, Sanfey, Rilling, Aronson, Nystrom, and Cohen (2003) show that humans, compared to machines, show stronger activation of bilateral anterior insula (regions associated with the experience of negative emotions) when receiving unfair offers in ultimatum games. This evidence suggests that people experience less emotion and spend less effort inferring mental states with machines than with humans (e.g., March 2021). These findings are consistent with research showing that humans feel less emotion toward machines than toward humans (Gray et al. 2007). It has been documented that denying others' minds or having a feeling that others are mentally inferior can lead to discrimination (Haslam 2006). In the context of human–machine interaction, Blascovich et al. (2002) also suggest that the lower the mental capacity perceived for a machine, the less likely the machine is to influence a human. de Melo and Gratch (2015) find that recipients in a dictator game expect more money from a machine than from another human and that proponents in an ultimatum game offer more money to a human recipient than to an artificial counterpart. The authors also show that people are more likely to feel guilt when interacting with a human than when interacting with a machine.

Cohn et al. (2021) pursue a question particularly close to our research question, in two experiments examining how human versus machine interaction influences cheating for financial gain. The results show that regardless of whether a machine has human capabilities, about three times as much fraud is committed when individuals interact with a machine rather than a human. In human interaction, individuals are particularly reluctant to report unlikely or suspicious outcomes. The second experiment shows that individuals who cheat prefer to interact with machines when faced with the opportunity to cheat. Their results suggest that human presence is key to curbing dishonest behavior.

We build on the simple cheating setting of Cohn et al. (2021) into a game-theory-based tax compliance setting. Our study examines whether taxpayer behavior changes, and more specifically, whether tax evasion occurs more frequently, depending on whether the tax auditor is a human or a computer. The tax auditors in most prior studies are not humans (or participants); instead, they are either devices or move systematically (and the taxpayers believe they do so). Although the tax auditing process in the real world is partially systematic, the final decisions are made by humans. Thus, it is important to examine whether taxpayers' behavior changes depending on their belief in the type of tax auditor.[3] More specifically, we make a clear distinction in our experimental condition, between a "computer auditor condition," in which the participants in the taxpayer role are told that the auditor is a computer that follows rules based on the model, and a "human auditor condition," in which the tax auditor is a participant. The experiment is designed so that the equilibrium of both conditions is the same. In other words, the only difference between these conditions is the taxpayer's belief in the type of tax auditor.

The main findings of this paper are as follows. First, our experimental results show that the taxpayer's reporting behavior is less tax compliant for a computer compared to a human auditor condition. This result is invaluable because there is a possibility that prior studies based on automated audits, which correspond to the computer condition in this paper, underestimate the level of tax compliance if taxpayers in the real world believe that the tax auditor is a human or equivalently that the tax audit is not automated.

Further, we also consider the two sub-hypotheses. One is regarding the link between belief in the type of tax auditor and the gender of participants. According to previous studies, women have often demonstrated better compliance than men (e.g., Bazart and Pickhardt 2009;

[3] Tan and Yim (2014) point out the importance of introducing a human auditor as its extension.

Gerxhani 2007; Grosch and Rau 2017; Gupta et al. 2020; Hasseldine 1999; Lewis, Carrera, Cullis, and Jones 2009; Mason and Calvin 1978; Porcano 1988; Spicer and Becker 1980; Spicer and Hero 1985; Vogel 1974; Wilson and Sheffrin 2005).[4] Differences in tax compliance between women and men can be attributed to differences in ethics (Chung and Trivedi 2003; Grasso and Kaplan 1998; Torgler and Valev 2006), as well as in risk propensity (for a general review, see Byrnes, Miller, and Schafer 1999). Compared to men, women are more likely to overestimate the probability of detection and the severity of the fine upon detection (Hasseldine 1999; Kinsey 1992; Richards and Tittle 1981; Smith 1992). Thus, we examine whether the impact imposed by the auditor type (human or computer) is greater in men than in women. The experimental results show that men evade tax payments more aggressively under the computer auditor condition than women.

The other hypotheses focus on whether tax compliance behavior is due to social preferences and social norms, such as prosociality and morality. As Alm and Torgler (2011) emphasize, it is crucial to consider the ethical aspects of individuals in order to understand tax compliance.[5] Taxpayers operate based on a wide range of personal moral standards. While some people have no qualms about not paying taxes or simply riding roughshod over others' tax payments, others may feel guilty or simply feel good about themselves for being conscientious enough to pay full taxes.[6] In particular, Christian and Alm (2014) focus on two moral emotions that have not been thoroughly examined in economics, particularly in the analysis of tax

[4] Some studies fail to find gender differences or observe that women are not generally more compliant than men. For instance, Kirchler and Maciejovsky (2001) assert that women's self-reported tax compliance is lower than that for men's. Friedland, Maital, and Rutenberg (1978) found women are more likely to evade taxes, but to a lesser extent than men. Chung and Trivedi (2003) found women are more compliant than men only after providing the sample with persuasive reasons to pay taxes. Wenzel (2002) found women to be more compliant with regard to reported income and deduction claims but with no gender differences regarding reports of extra income. Torgler and Schneider (2004) report higher tax morals for women than men in Switzerland and Belgiumbut minor differences in Spain. It has to be noted that results indicating no differences between women and men are often not published (Unger, 1979). Although empirical findings are mixed, when there are significant gender differences, women are more compliant than men.

[5] In a study on tax morals or ethics and tax compliance, for example, Kaplan et al. (1997) tests the effects of moral reasoning and educational communication on tax evasion intentions in an experiment. Their results indicate that taxpayers who use high moral reasoning in their decision making have significantly lower tax evasion intentions. Further, Henderson and Kaplan (2005) propose and test a model of tax compliance with the goal of identifying the mechanisms by which ethical beliefs influence tax compliance behavior.

[6] In fact, there is some evidence that morality influences the way individuals make decisions, particularly with regard to tax payments (Baldry 1986; Coricelli, Joffily, Montmarquette, and Villeval 2010; Schwartz and Orleans 1967).

compliance: sympathy and empathy. "Empathy" is the emotional state of "putting oneself in another's shoes," in which an individual is able to identify with the same or similar emotions of the other (Batson and Coke, 1981). "Sympathy" is considered to be an emotional response of sadness or concern for the other person's well-being caused by the other person's emotions, a response that is not necessarily identical to the other person's emotions. In order to identify participants' sympathy, the authors use questionnaires about the frequency of their engagement in prosocial behavior, and they suggest that the presence of sympathy in most cases encourages tax compliance. In a similar study, Grosch and Rau (2017) experimentally analyze the role of individual prosociality on honest behavior using the social value orientation (SVO) measure. They detect a positive correlation between participants' SVO angle (degree of prosociality) and honest behavior. According to their study, we developed our hypothesis to consider the change in tax compliance behavior of prosocial participants in relation to the auditor type. Our results show that participants with prosocial tendencies pay more tax when the auditor is a human because they feel sympathy toward the auditor.

Our study contributes to the tax compliance literature, especially from the standpoint of policymaking in the digital age. The result suggests that the belief that decisions in a tax audit are made by humans makes taxpayer reporting more tax compliant. In other words, to facilitate higher levels of tax compliance from taxpayers it might be preferable not to manage the rules in a mechanically uniform manner. This paper also benefits tax audit policy in the real world. The IRS has asserted that "one of the tools in the arsenal of the IRS which promotes voluntary compliance is the uncertainty in the minds of the taxpayers as to just how much overstepping of the boundaries of strict compliance will bring down the enforcement authority of the agency."[7] Although it is well known that the IRS uses a formula (called the DIF) for selecting tax returns, this formula is highly classified by the IRS. In contrast, the tax agency in Italy adopted a

[7] *Roberts v. IRS,* 584 *Federal Supplement* 1241 (Eastern District, Michigan), 1984.

peculiar audit rule (called “Studi di Settore”) in 1998 and reveals a part of the information incorporated in the audit rule.[8] The degree of the disclosure policy by the tax authority would affect the taxpayer’s belief concerning the extent of automation and flexibility used by the tax auditor, which in turn would affect their tax compliance behavior.

The remainder of the paper is organized as follows. Section 2 introduces the development of the analytical model and explains our hypotheses. Section 3 shows our research design. Section 4 presents the experimental results. Lastly in Section 5, we discuss our results and provide a conclusion.

2. THEORY AND HYPOTHESES

We describe the specified model of Reinganum and Wilde (1986) that is used as a benchmark for this study. To date, there have been many analytical studies on tax compliance. The analysis of tax evasion activities goes back to the seminal contributions of Allingham and Sandmo (1972), Srinivasan (1973), and Yitzhaki (1974). These studies assume that individuals conduct their own cost–benefit analysis of paying or evading taxes, exclusive of any contact with other taxpayers. Considering the audit or detection probability as well as the penalty, taxpayers decide how much of their tax payments they should actually pay. These authors confirm that increases in these variables have positive effects on tax compliance (i.e., tax evasion is reduced).[9]

The auditor’s behavior has received attention as an extension of the simple tax evasion model. A weakness of the Allingham–Sandomo model is that it assumes that audit probability is constant. However, in the real world, it is natural to consider that audit probability depends on the amount of income reported and/or the variables of tax enforcement. Using a game-theory-

[8] See Santoro and Fiorio (2011).

[9] More precisely, the effect of raising the tax rate on tax evasion is ambiguous because it has two effects. First, it lowers after-tax income has been received from full compliance, which should make people more risk averse regarding the amount of tax evasion, and, consequently, less likely to accept more cheating. However, as the tax rate rises, the return on tax evasion increases, while the penalty of detection remains unchanged. However, Yatzhaki (1974) observes that if the penalty is proportional to the amount of tax evaded, then the model predicts that cheating will decrease when the tax rate increases.

based model between taxpayers and auditors, Graetz et al. (1986) and Reinganum and Wilde (1986) develop a more general theoretical framework in which the audit probability is a function of reported income, which is determined by the amount of tax evasion as an equilibrium. This framework has been used not only to generate predictions in tax compliance but also for determining a tax auditor's optimal audit strategy.

Even though there has been a growing number of analytical studies, we examine the specified model of Reinganum and Wilde (1986) in this paper for two reasons.[10] First, Reinganum and Wilde (1986) present one of the earliest and simplest game-theory-based models of tax compliance and enforcement. Thus, their mathematical framework is quite tractable for our experiments and easily understandable for participants. Second, the true income in their model is a continuous variable (not binary), that is, the amount of tax evasion in equilibrium would depend on the true income.[11]

The game comprises a risk-neutral taxpayer and a risk-neutral tax auditor in correspondence.[12] The taxpayer's true income is their private information that cannot be observed by the tax auditor. Based on their true income, the taxpayer reports the taxable income to the tax auditors. As the tax auditors do not know the true income of the taxpayer, they estimate it from the reported income and decide how much effort they should exert on the tax audit. The auditor's effort level determines the audit probability of the true income in the tax audit; the higher the effort level exerted on the tax audit, the greater the probability of verifying the true income.

[10] For example, Mookherjee and P'ng (1989), Beck, Davis, and Jung (1991), Sansing (1993), and Cronshaw and Alm (1995) use interactive models of tax compliance. More recently, Gahramanov (2009) adopts an alternative assumption on the relationship between tax rate and penalties. Another extension is from a partial static model to a dynamic one, as in Dalamagas (2011), which incorporates the Allingham–Sandomo model into a neoclassical growth model to make it dynamic, and analyzes the effects of tax enforcement policies, taking into account the average tax burden on the economy.
[11] Graetz et al. (1986) assume true income to be a binary variable. Since low-type taxpayers have no incentive to cheat on their reports, they analyze the tax evasion decisions of high-type taxpayers. In this model, the tax evasion decision is "to do" or "not to do," and thus it is difficult to measure the amount of tax evasion. Furthermore, whether taxpayers cheat or not does not depend on their true income because the cheaters are always low type.
[12] The preference for risk has an impact on equilibrium values. Therefore, when we compare analytical and experimental results, we attempt to control the participants' risk preferences by giving them spreadsheets as a benchmark for calculating the risk-neutral payoff.

Reported income and audit probability in equilibrium with our experimental parameters are summarized in Table 1,[13] which shows that the reported income in equilibrium is lower when true income is lower. Further, the equilibrium audit probability is convex with respect to the reported income. In other words, if the reported income is higher, the marginal probability change is also higher. A likely explanation for this characteristic is as follows. When a taxpayer evade tax payments at a relatively low income, they incur more evasion costs because the tax evasion is easily verified in this case owing to high audit probability. Therefore, the taxpayers' benefit from tax evasion is lower at a relatively low compared to a relatively high income. Consequently, the tax auditor does not have an incentive to increase the effort level to verify the tax evasion for low reported income.

(Insert Table 1 about here.)

This theoretical framework provides the prediction for our experimental tests. Theoretically, the reported income should be the same regardless of whether the tax auditor is a human (participant) or a computer since the information set of the taxpayer is equivalent under both conditions. Related studies in which people make important distinctions between machines and humans (e.g., Castelo et al. 2019; Cohn et al. 2021; Dietvorst et al. 2018; Ishowo-Oloko et al. 2019), however, suggest the possibility that a player's belief changes depending on whether their playing partner is identified as a human or a computer. In our experiment, there are two conditions: (1) the tax auditor is a human (i.e., a participant), and (2) the tax auditor is a computer that follows rules based on the model. We examine whether the level of tax compliance differs between these two conditions.

We next generate the hypothesis concerning whether there is a behavioral difference

[13] Derivation of equilibrium and setting of parameters are presented in detail in Appendix A.

when the other player is a computer or a human. A review of the literature indicates a human aversion to, and trust in algorithms; and a diffusion of responsibility between humans and machines. For example, March (2021) reviews 162 experimental studies using computer players and finds that behavior and the outcomes of strategic interaction often change when humans interact with computer players rather than other humans. In particular, humans usually adapt to computer players even when detailed prior information about them is absent – they often act more selfishly and more rationally in their presence, and apply different cognitive processes.

Related research by Cohn et al. (2021) and de Melo and Gratch (2015) ask similar questions to our research question. In two experiments examining how human versus machine interaction influences cheating for financial gain, Cohn et al. (2021) find that individuals are about three times more likely to cheat when interacting with a machine than a human, regardless of whether the machine has human capabilities. de Melo and Gratch (2015) find that people are more likely to feel guilty when interacting with a human counterpart than when interacting with a machine.

Summarizing the arguments, although people treat computers similarly to human partners, people are likely to experience less guilt when interacting with a computer. Drawing from our main hypothesis regarding the tax auditor type and tax compliance, it is reasonable to speculate that people experience less guilt or have less social image concern regarding tax evasion when dealing with a computer compared to a human tax auditor. Accordingly, we formulate the first hypothesis.

***Hypothesis 1*: **People evade more tax payments when the tax auditor is a computer rather than a human.

We also consider the sub-hypothesis regarding the link between the auditor type and the gender of participants. Previous studies indicate that women are generally more compliant concerning tax than men (e.g., Bazart and Pickhardt 2009; Gerxhani 2007; Grosch and Rau 2017; Gupta et al. 2020; Hasseldine 1999; Lewis, Carrera, Cullis, and Jones 2009; Mason and Calvin 1978; Porcano 1988; Spicer and Becker 1980; Spicer and Hero 1985; Vogel 1974; Wilson and Sheffrin 2005). Differences in tax compliance between women and men can be attributed to differences in ethics, as well as risk propensity. Compared to men, women are more likely to overestimate the probability of detection of tax evasion and the severity of the consequent fine.

Hypothesis 1-1**:** Men are more likely to engage in tax evasion than women when the tax auditor is a computer.

Other aspects known to influence tax compliance behavior include social preferences and social norms, such as prosociality and morality. Christian and Alm (2014) focus on two moral aspects related to emotions that have not been extensively examined in economics, particularly in the analysis of tax compliance: sympathy and empathy. “Empathy” is the emotional state of “putting oneself in another’s shoes,” in which an individual is able to identify with the same or similar emotions as the other. In order to determine presence of participants’ sympathy, these authors use questions about frequency of engagement in prosocial behaviors and suggest that the presence of sympathy in most cases encourages more tax compliance. Grosch and Rau (2017) experimentally analyze the role of individual prosociality in honest behavior using the SVO (social value orientation) measure.[14] They detect a positive correlation between participants’ SVO angle (the extent of prosociality) and their honest behavior.

According to their studies, the extent of individual prosociality has an impact on taxpayer’s tax compliance behavior. We build on their hypothesis to consider that the tax

[14] This measure reflects people’s magnitude of concern for other people’s payoffs. Here, participants make decisions on payoff distributions for themselves and another person. Based on these decisions, an individual SVO angle can be calculated for each participant.

compliance behavior of prosocial participants depends on the auditor type. In other words, participants who demonstrate high prosocial tendencies are more willing to pay tax when the auditor is a human than a computer because they are more likely to feel sympathy toward the human auditor than the computer auditor. Thus, we propose the following sub-hypothesis.

Hypothesis 1-2**:** Participants who demonstrate high prosocial tendencies are less likely to evade tax than those showing low prosocial tendencies when the tax auditor is a human.

3. EXPERIMENTAL DESIGN AND PROCEDURE

3.1. Experimental Design

We tested our hypotheses using an experiment involving the tax compliance game described in the previous section. We adopted a 2 × 1 experimental design, in which the type of auditor was manipulated between participants at two levels: computer and human auditor conditions.

The laboratory experiment was programmed using Z-Tree software (Fischbacher 2007) and conducted in an experimental laboratory at a large university in January 2019.[15] A total of 116 graduate and undergraduate student participants were recruited from the campus through the laboratory's website.[16] A total of 11 sessions of computerized experiments were conducted: five for the computer condition and six for the human condition.

Participants were 20.56 years old on average [standard deviation (SD) = 1.23]. The maximum and minimum ages of participants were 25 and 19 years, respectively, and 54.3% of the participants were women. We incentivized participation through monetary rewards. The

[15]The experiments in this study have been approved by the IRB of the university in which this experiment was conducted.
[16] The use of students as surrogates for employed adults and professionals has long been an issue in business research (Dickhaut, Livingston, and Watson 1972). However, several studies have suggested that the use of business students to proxy for professionals is appropriate when assessing basic traits or perceptions (Ward 1993). For example, Remus (1986) and Greenberg (1987) addressed the student surrogate issue by studying both business students and employed adults simultaneously, and both studies conclude that there are no differences between the business students and the employed adults. Geiger and Smith (2010) also argue that the use of business students as surrogates for employed professionals is appropriate.

participants were randomly allocated to each condition: human condition, n = 76; and computer condition, n = 40. Since we adopted a between-subject design, no participant participated in more than one experimental session.

3.2. Procedures

Under the human condition, participants were assigned the role of taxpayers (n = 38) or auditors (n = 38) as predetermined randomly and anonymously by computer at the beginning of the experiment. Under the computer auditor condition, all participants were assigned the role of taxpayers (n = 40). Roles remained unchanged throughout the experimental session. Under the human auditor condition, we used a random matching protocol for participants to eliminate the bias of reputation building in a repeated game. We informed all of the participants that a computer randomly determined their partner. The two roles were labeled as "Taxpayer" and "Tax auditor" in the experimental instructions. Our study employed a contextually rich tax compliance game setting, rather than an abstract economic game. A distinct advantage of this choice is that it reduces the potential for participants viewing the experiment as a game, which could encourage opportunism (Hannan, Rankin, and Towry 2006; Haynes and Kachelmeier 1998).[17]

The participants were separated by dividers in each experimental session. At the beginning of each experimental session, the experimenter read an initial set of instructions aloud to participants, while the participants followed along on their own copies of the instructions (see Appendix C). The structure of the game was explained to the participants. After the instructions were read, participants were asked to answer questions about the experiment. Participants had to answer all questions correctly before they were able to commence an experimental task. Hence, all participants accurately understood the details of the experiment. Figure 1 represents the

[17] Trivedi and Chung (2006) examine whether the use of tax-specific instructions results in differences in income reporting behavior in comparison to the use of context-free instructions.

timeline of the game and Figure 2 shows the screens of the taxpayers' and tax auditors' decisions.

[insert Figure 1 and Figure 2 about here.]

We distributed a "recommended audit probability" list to all participants as a decision aid (see Appendix D). This list involved a table illustrating the equilibrium probabilities of audit for reported incomes to control the influence of the probability of audit between two conditions. In our experiments, under the computer condition, the participants in the taxpayer role are told that the auditor is a computer that follows rules based on the list. Under the human condition, all participants both taxpayers and tax auditors are told that they may use the list as a decision aid.

The feedback information at the end of each round was as follows: his/her own action, whether a tax audit is conducted, and his/her own payoff. During all the treatments, participants received no information, individually or in aggregate, about the results of the other pairs of participants.

The experiment parameters were standardized for both conditions as follows. To control for the realizations of true income across sessions, we chose one set of the 20-period true income realizations before the first experiment and applied it to every session.

At the end of the experiment, participants filled out an exit questionnaire concerning demographic information and personal perceptions. Each session lasted about 70 minutes including the time for instruction.[18] Participants received a JPY 1000 show-up fee plus their earnings from the game in cash. The average earnings were JPY 2418: JPY 2406 for the human condition and JPY 2439 for the computer condition.[19] Table 2 summarizes the experimental

[18] Of the 70 minutes participants spent on the experiment, 15 minutes were allocated for instructions, 40 minutes for the actual experimental task, and 15 minutes for the post-experiment questionnaire.
[19] The minimum hourly wage in Tokyo is currently about JPY1000 (Ministry of Health, Labour and Welfare of Japan 2021). Therefore, the average amount participants received for a single 70-minute-session is 2 to 3 times more than the amount students usually receive for their part-time work.

design.

[Insert Table 2 about here]

4. RESULTS

4.1. Summary Statistics

Table 3 reports the descriptive statistics of the compliance rate of taxpayers by each experimental condition:[20] Panel A presents the compliance rate by condition and gender and Panel B shows the compliance rate by condition and prosociality.[21]

[Insert Table 3 about here.]

Panel A of Table 3 shows that the compliance rate was higher under the human condition (78.1%) than the computer condition (76.1%). In addition, Panel A also indicates that the rate is different due to the difference in gender. Panel B shows that, under both computer and human conditions, each compliance rate was higher for participants determined as "prosocial type" (computer, 77.6%; human, 84.5%) than those who were not (computer, 75.1%; human, 76.7%). Figure 3 presents the mean levels of the compliance rate for each condition by period.

[Insert Figure 3 about here.]

Despite the influence of differences in true incomes, the first and second halves of the

[20] To test the effectiveness of our experimental manipulations and controls, participants responded to the exit questionnaire. After the experiment, participants responded to a number of statements on the exit questionnaire that were designed to test the effectiveness of our experimental manipulations and controls using a seven-point Likert-type scale: 1 = Strongly disagree to 7 = Strongly agree. Tests of manipulations and controls are the mean difference from the neutral response of 4 (all $p < 0.01$). Therefore, we find evidence that our experimental manipulations and controls are effective.

[21] We use the SVO, which is the measure of prosociality presented by Van Lange, Otten, De Bruin, and Joireman (1997). This measure reflects people's magnitude of concern for other people's payoffs. Here, participants make decisions on payoff distributions for themselves and another person. Based on these decisions, an individual SVO angle (prosocial, individualistic, and competitive orientations) can be calculated for each participant.

round do not differ for all conditions (Figure 3). Hence, it is reasonable to conclude a limited influence of any learning effect and that our experimental design succeeded in controlling functions.

4.2. Regression

To check the hypotheses in Section 2, we perform several regression analyses. To explore the relationship between auditor type (computer or human) and tax compliance, we assume the following basic relation:

$$Comp_{it} = F\ [PCD_i; PCD_i \times GEN_i; PCD_i \times PRO_i; X_{it}; TD_t],$$

where $Comp_{it}$ represents the portion of income declared (ratio of declared to actual income) and PCD_i is a dummy variable that takes 0 if the experiment is under the human auditor condition and 1 if under the computer auditor condition. According to our hypotheses, the tax compliance behavior affected by auditor type differs depending on the characteristics of taxpayers. More specifically, the male and/or more prosocial participants are less tax compliant under the computer auditor condition than the female and/or less prosocial participants. We control for several factors (X_{it}), including the natural logarithm of true income [$Ln\ (TI)_t$] and whether the participant was audited ($Audited_{t-1}$) or punished in the previous round ($Fine_{t-1}$), which takes potentially longer lasting effects into account.

We also control for other individual characteristics identified in the literature, including gender (GEN, dummy for women), the degree of prosocial behavior (PRO), the score on dark triad traits ($Dark$), and the score of the Moral Foundations Questionnaire (*MFQ*); *PRO* is a dummy variable that takes 1 if the participant shows prosocial tendencies using the SVO, which is the measure of social preferences created by Van Lange, Otten, De Bruin, and Joireman (1997), and 0 otherwise. *Dark* expresses the total score of the Dark Triad Dirty Dozen measure that Jonason and Webster (2010) provide. The dark triad consists of three factors: narcissism, Machiavellianism, and psychopathy. These three traits are representative of antisocial personality (Paulhus and Williams 2002). *MFQ* expresses the total score of the moral foundations questionnaire, which is designed to assess the extent to which people prioritize five foundational domains of moral decision-making: Harm/Care, Fairness/Reciprocity, Ingroup/Loyalty, Authority/Respect, and Purity/Sanctity (Graham et al. 2011). Finally, we control for time dynamics (time dummies, TD_t).

Table 4 contains our regression results.[22]

[Insert Table 4 about here.]

The difference between regressions (1) and (2) lies in whether they include the cross-terms, $PCD_i \times GEN_i$ and $PCD_i \times PRO_i$. Our estimations indicate a significant negative relationship between tax compliance and computer auditor condition. For regressions (1) and (2), the coefficient is significant at $p < 0.01$, showing that the participants are less tax compliant under the computer auditor condition than the human auditor condition. This result supports H1. Our results also indicate that the experience of having been audited in the previous period promotes tax compliance whereas having been punished in the previous period makes taxpayers less tax compliant. In terms of individual characteristics, people who demonstrate higher prosocial tendencies and/or lower *MFQ* score are likely to be more tax compliant. Further, regression (2) shows that female participants are significantly more compliant under the computer auditor condition at $p < 0.01$ and also shows that participants with prosocial tendencies are significantly more compliant under the human auditor condition at $p < 0.01$. These results support H1-1 and H1-2.

In regressions (3) and (4), we divide our sample into male and female participants [male subsample is (3)]: Regressions (3) and (4) indicate that male participants are less compliant

[22] The descriptive statistics, Pearson correlations of our experimental data, and the definition of variables are summarized in Appendix B.

under the computer auditor condition while female participants are more compliant. This result supports H1-1. We also find that, although the compliance rate of female participants is significantly positively correlated with the experience of having been audited in the previous period, this is not the case for male participants.

We divide our sample into prosocial and non-prosocial groups [regressions (5) and (6)]: Regressions (5) and (6) indicate that participants in the non-prosocial group are significantly less compliant under the computer auditor condition at $p < 0.01$; although participants in the prosocial group are not. This result supports H1-2.

With respect to the other variables, the participants whose true income is higher are less tax compliant than those whose income is lower. This is intuitively suggested by the fact that people with higher income have more options to evade tax payment. While prior experience in having been audited improves tax compliance [although non-significant in regressions (3) and (6)], a penalty paid in the previous period seems to lower tax compliance. This result is difficult to explain but is consistent with the results of Dulleck et al. (2016). Significant negative relationships observed in all regressions for the coefficient of *TD* reveals that participants grow less tax compliant as the rounds proceed.[23]

In summary, the regression analysis generally supports our hypotheses. The outline of our findings are as follows: (1) participants are more likely to engage in tax evasion when the tax auditor is a computer rather than human, (2) men are more likely than women to engage in tax evasion in the computer condition, and (3) prosocial participants are more tax compliant than non-prosocial participants in the human auditor condition.[24]

5. CONCLUDING REMARKS

[23] According to the correlation matrix (Table B2), the Pearson correlation coefficient between the prior audit and the previously fined is quite high (0.8). However, the Variance Inflation Factor in the regressions is at most less than 4. Further, we also test regressions without each of $Audited_{t-1}$ and $Fined_{t-1}$. Although the level of significance differs in Table 4, the signs are similar.

[24] See also Appendix E in which we analyze the taxpayer's risk perception of tax audit under both conditions.

The purpose of this study is to experimentally investigate whether there is a difference in tax compliance behavior of the taxpayer if the tax auditor is a human (participant) or a computer (experimenter), by applying a game-theory-based situation. Although there have been many empirical studies focusing on tax audit rules, there is still room for research on taxpayer compliance in relation to their belief concerning the tax auditor type. We build on the simple cheating setting in Cohn et al. (2021) and create a game-theory-based tax compliance setting. Our study examines whether taxpayer behavior changes, and more specifically, whether tax evasion increases, based on whether the tax auditor is a human or a computer. The tax auditors in most prior studies are not humans; instead, they are either machines or taxpayers are led to believe that they are machines. However, although the tax auditing process in the real world is partially automated, the final decision is made by humans. Thus, it is important to examine whether taxpayers' behavior changes based on their belief concerning the type of tax auditor. More specifically, we made a distinction between the experimental condition involving a "computer auditor condition," in which the tax auditor is operated by an experimenter, and a "human auditor condition," in which the tax auditor is a participant. We design the experiment in this manner so that the equilibrium of both conditions remains the same, that is, the only difference between these conditions is the taxpayer's belief concerning the type of tax auditor.

The experimental results indicate that taxpayers' reporting behavior under the computer auditor condition is less compliant than under the human auditor condition. Our experiment successfully replicates the results of Cohn et al. (2021) using a tax compliance setting. This result is also consistent with prior studies that focus on the relationship between the uncertainty of tax audit and tax compliance behavior. Furthermore, our experiments show that men are more likely to engage in tax evasion than women in the computer auditor condition, and participants with prosocial tendencies are more tax compliant in the human auditor condition.

The result of this paper also contributes to tax audit policy by providing a guide for how much of a formula should be used by a tax authority and how much of that formula should be disclosed to taxpayers. Our results show that taxpayers who believe that the tax audit system is automated are less tax compliant. Thus, in order to ensure reliable collection of tax revenue, it is important for the tax authority to present an impression to taxpayers that the tax audit is conducted by a human auditor regardless of the actual process employed.

Despite its contributions, this study has several limitations including those that are inherent to the use of a controlled experiment, so caution is recommended when extrapolating our experimental results to real-world situations.

References

Accounting Today.com. 2016. *The audit of the future.* (April 14). Available at: https://www.accountingtoday.com/the-audit-of-the-future

Allingham, M. G., and A. Sandmo. 1972. Income tax evasion: A theoretical analysis. *Journal of Public Economics* 1 (3): 323–338.

Alm, J., 2012. Measuring, explaining, and controlling tax evasion: lessons from theory, experiments, and field studies. *Tax Public Finance* 19 (1): 54–77.

Alm, J., and M. McKee. 2004. Tax compliance as a coordination game. *Journal of Economic Behavior and Organization* 54 (3): 297–312.

Alm, J., G. H. McClelland, and W. D. Schulze. 1992. Why do people pay taxes? *Journal of Public Economics* 48 (1): 21–38.

Alm, J., M. B. Cronshaw, and M. McKee. 1993. Tax compliance with endogenous audit selection rules. *Kyklos* 46 (1): 27–45.

Alm, J., and Torgler, B. 2011. Do ethics matter? Tax compliance and morality. *Journal of Business Ethics* 101(4): 635–651.

Baldry, J. C. 1986. Tax evasion is not a gamble: A report on two experiments. *Economics Letters 22*(4): 333-335.

Batson, C. D., and Coke, J. S. 1981. Empathy: A source of altruistic motivation for helping? In J. P. Rushton and R. M. Sorrentino (Eds.), *Altruism and helping behavior: Social, personality, and developmental perspectives* Hillsdale, NJ: Erlbaum: 167–211.

Bazart, C., & Pickhardt, M. 2009. Fighting income tax evasion with positive rewards: Experimental evidence. *Research Document* (2009-01).

Beck, P. J., J. S. Davis, and W. O. Jung. 1991. Experimental evidence on taxpayer reporting under uncertainty. *The Accounting Review* 66 (3): 535–558.

Berg, J., J. Dickhaut, and K. McCabe. 1995. Trust, reciprocity and social history. *Games and Economic Behavior* 10 (1): 122–142.

Blascovich, J., Loomis, J., Beall, A. C., Swinth, K. R., Hoyt, C. L., and Bailenson, J. N. 2002. Immersive virtual environment technology as a methodological tool for social psychology. *Psychological inquiry* 13(2): 103-124.

Brandts, J. and G. Charness. 2011. The strategy versus the direct-response method: a first survey of experimental comparisons. *Experimental Economics* 14 (3): 375–398.

Brennan, B., M. Baccala, and M. Flynn. 2017. *Artificial intelligence comes to financial statement audits.* (February 2). Available at: http://ww2.cfo.com/auditing/2017/02/artificial-intelligence-audits/

Byrnes, J. P., Miller, D. C., and Schafer, W. D. 1999. Gender differences in risk taking: A meta-analysis. *Psychological Bulletin* 125: 367–383.

Castelo, N., M. W. Bos, and D. R. Lehmann. 2019. Task-dependent algorithm aversion. *Journal of Marketing Research* 56(5), 809-825.

Christian, R. C., and Alm, J. 2014. Empathy, sympathy, and tax compliance. *Journal of economic psychology 40*: 62-82.

Chung, J., and Trivedi, V. U. 2003. The effect of friendly persuasion and gender on tax compliance behavior. *Journal of Business Ethics* 47: 133–145

Clark, J., L. Friesen, and A. Muller. 2004. The Good, the bad, and the regulator: An experimental test of two conditional audit schemes. *Economic Inquiry* 42(1): 69–87.

Cohn, A., T. Gesche, and M. A. Maréchal. 2021. Honesty in the digital age. *Management Science* (forthcoming).

Commerford, B.P., S.A. Dennis, J.R. Joe, and J.W. Ulla. 2021. Man versus machine: Complex estimates and auditor reliance on artificial intelligence. *Journal of Accounting Research* (forthcoming).

Coricelli, G., Joffily, M., Montmarquette, C., and Villeval, M. C. 2010. Cheating, emotions, and rationality: an experiment on tax evasion. *Experimental Economics 13*(2): 226-247.

Cronshaw, M. E., and J. Alm. 1995. Tax compliance with two-sided uncertainty. *Public Finance Quarterly* 23 (2): 139–166.
Cummings, R. G., J. Martinez-Vazquez, M. McKee, and B. Torgler. 2006. *Effects of tax morale on tax compliance: experimental and survey evidence.* Working paper, University of California Berkeley. Berkeley Program in Law and Economics. Available at: https://escholarship.org/uc/item/8sh2w9fp
Dalamagas, B. 2011. A dynamic approach to tax evasion. *Public Finance Review* 39 (2): 309–326.
de Melo, C. M., and J. Gratch. 2015. *People show envy, not guilt, when making decisions with machines.* International Conference on Affective Computing and Intelligent Interaction (ACII). IEEE: 315–321. doi: 10.1109/ACII.2015.7344589
Dickhaut, J., W. J. Livingston, and D. Watson. 1972. On the use of surrogates in behavioral experimentation. *The Accounting Review* 47: 455–470.
Dulleck, U., Fooken, J., Newton, C., Ristl, A., Schaffner, M., and Torgler, B. 2016. Tax compliance and psychic costs: Behavioral experimental evidence using a physiological marker. *Journal of Public Economics 134*: 9-18.
Fischbacher, U. 2007. z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental economics* 10(2): 171-178.
Friedland, N., Maital, S., and Rutenberg, A. 1978. A simulation study of income tax evasion. *Journal of Public Economics* 10: 107–116.
Friedman, 1995. *"It's the computer's fault"—Reasoning about computers as moral agents.* Conference Companion on Human Factors in Computing Systems (CHI 95). Association for Computing Machinery, New York, NY, pp. 226–227. doi:10.1145/223355.223537
Gahramanov, E. 2009. The theoretical analysis of income tax evasion revisited. *Economic Issues* 14 (1): 35–41.
Gallagher, H. L., Jack, A. I., Roepstorff, A., and Frith, C. D. 2002. Imaging the intentional stance in a competitive game. *Neuroimage* 16(3): 814-821.
Geiger, M., and J. L. Smith. 2010. The effect of institutional and cultural factors on the perceptions of earnings management. *Journal of International Accounting Research* 9(2): 21-43.
Gerxhani, K. 2007. Explaining gender differences in tax evasion: The case of Tirana, Albania. *Feminist Economics* 13: 119–155.
Gogoll, J. and M. Uhl. 2018. Rage against the machine: Automation in the moral domain. *Journal of Behavioral and Experimental Economics* 74: 97-103.
Graetz, M. J., J. F. Reinganum, and L. L. Wilde. 1986. The tax compliance game: Toward an interactive theory of law enforcement. *Journal of Law, Economics and Organization* 2(1): 1–32.
Graham, J., B. A. Nosek, J. Haidt, R. Iyer, S. Koleva, and P. H. Ditto. 2011. Mapping the moral domain. *Journal of Personality and Social Psychology* 101, 366–385.
Grasso, L., and Kaplan, S. E. 1998. An examination of ethical standards. *Journal of Accounting Education* 16: 85–100.
Gray, H. M., Gray, K., and Wegner, D. M. 2007. Dimensions of mind perception. *Science* 315(5812): 619-619.
Greenberg, J. 1987. The college sophomore as guinea pig: Setting the record straight. *Academy of Management Review* 12 (1): 157–159.
Grosch, K., and H. A. Rau. 2017. Gender differences in honesty: The role of social value orientation. *Journal of Economic Psychology* 62, 258-267.
Gupta, V. K., S. Mortal, B. Chakrabarty, X. Guo, and D. B Turban. 2020. CFO gender and financial statement irregularities. *Academy of Management Journal* 63(3): 802-831.
Haidt, J., and J. Graham. 2007. When morality opposes justice: Conservatives have moral intuitions that liberals may not recognize. *Social Justice Research* 20: 90–116.

Hannan, R. Y., F. W. Rankin, and K. L. Towry. 2006. The Effect of information systems on honesty in managerial reporting: A behavioral perspective. *Contemporary Accounting Research* 23(4): 885–918.

Haslam, N. 2006. Dehumanization: An integrative review. *Personality and social psychology* review 10(3): 252-264.

Hasseldine, J. 1999. Gender differences in tax compliance. *Asia-Pacific Journal of Taxation* 3: 73–89.

Haynes, C. M., and S. J. Kachelmeier. 1998. The effects of accounting contexts on accounting decisions: A synthesis of cognitive and economic perspectives in accounting experimentation. *Journal of Accounting Literature* 17: 97–136.

Henderson, B. C., and S. E. Kaplan. 2005. An examination of the role of ethics in tax compliance decisions. *Journal of the American Taxation Association* 27(1), 39-72.

Ishowo-Oloko, F., J. F. Bonnefon, Z. Soroye, J. Crandall, I. Rahwan, and T. Rahwan. 2019. Behavioural evidence for a transparency–efficiency tradeoff in human–machine cooperation. *Nature Machine Intelligence* 1(11): 517-521.

Jonason, P. K., and G. D. Webster. 2010. The dirty dozen: A concise measure of the Dark Triad. *Psychological Assessment* 22: 420–432.

Kaplan, S. E., K. J. Newberry, and P. M. Reckers. 1997. The effect of moral reasoning and educational communications on tax evasion intentions. *The Journal of the American Taxation Association*, 19(2), 38.

Katagiri, Y., C. Nass, and Y. Takeuchi. 2001. Cross-cultural studies of the computers are social actors paradigma: the case of reciprocity. In *Evaluation and Interface Design, volume 1 of Human Factors and Ergonomics,* edited by M.J. Smith, R.J. Koubeck, G. Salvendy, and D. Harris, pp. 1558–1562. Mahwah, N.J. and London: Lawrence Erlbaum.

Kim, C. K., and W. S. Waller. 2005. A behavioral accounting study of strategic interaction in a tax compliance game. In *Experimental Business Research,* edited by R. Zwick and A. Rapoport, 35–56. Boston, MA: Springer.

Kinsey, K. A. 1992. Deterrence and alienation effects of IRS enforcement: An analysis of survey data. In J. Slemrod (Ed.), *Why people pay taxes: Tax compliance and enforcement* Ann Arbor, MI: University of Michigan Press: 259–285

Kipp, P.C., M.B. Curtis, and Z. Li. 2020. The attenuating effect of intelligent agent and agent autonomy on manager's ability to diffuse responsibility for and engage in earnings management. *Accounting Horizon* 34(4): 143-164.

Kirchkamp, O., and C. Strobel. 2019. Sharing responsibility with a machine. *Journal of Behavioral and Experimental Economics* 80, 25-33.

Kirchler, E., and Maciejovsky, B. 2001. Tax compliance within the context of gain and loss situations, expected and current asset position, and profession. *Journal of Economic Psychology* 22: 173–194.

Lewis, A., Carrera, S., Cullis, J., and Jones, P. 2009. Individual, cognitive and cultural differences in tax compliance. UK and Italy compared. *Journal of Economic Psychology* 30: 431–445.

March, C. 2021. Strategic interactions between humans and artificial intelligence: Lessons from experiments with computer players. *Journal of Economic Psychology* 87:102426. doi:10.1016/j.joep.2021.102426

Mason, R., and Calvin, L. D. 1978. A study of admitted income tax evasion. *Law and Society Review* 13: 73–89.

Ministry of Health, Labour and Welfare of Japan. 2021. *Chiikibetsu saitei chingin no zenkoku ichiran [Minimum hourly wages across the regions: Fiscal year 2021].* Available at: https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/koyou_roudou/roudoukijun/minimumichiran/

Mookherjee, D., and I. P'ng. 1989. Optimal auditing, insurance, and redistribution. *Quarterly Journal of Economics* 104 (2): 399–415.

Moon, Y., 2003. Don't blame the computer: when self-disclosure moderates the self-serving bias. *Journal of Consumer Psychology* 13 (1-2): 125–137.
Moon, Y., and C. Nass. 1998. Are computers scapegoats? Attributions of responsibility in human–computer interaction. *International Journal of Human-Computer Studies* 49 (1): 79–94. doi:10.1006/ijhc.1998.0199
Nass, C., and Y. Moon. 2000. Machines and mindlessness: Social responses to computers. *Journal of Social Issues* 56(1): 81-103.
Nass, C., B. J. Fogg, and Y. Moon. 1996. Can computers be teammates? *International Journal of Human-Computer Studies* 45 (6): 669–678.
Nass, C., J. Steuer, E. R. Tauber, B. Adelson, S. Dumais, J. Olson. 1994. *Computers are social actors.* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. Association for Computing Machinery, New York, pp. 72–78. doi:10.1145/259963.260288
Paulhus, D. L., and Williams, K. M. 2002. The dark triad of personality: Narcissism, Machiavellianism, and psychopathy. *Journal of research in personality 36*(6): 556-563.
Petersen, M. A. 2007. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies* 21(1): 435-480.
Porcano, T. M. 1988. Correlates of tax evasion. *Journal of Economic Psychology* 9: 47–67.
Rahwan, I., J. W. Crandall, and J. F. Bonnefon. 2020. Intelligent machines as social catalysts. *Proceedings of the National Academy of Sciences* 117(14): 7555-7557.
Reeves, B., and C. Nass. 2003. *The Media Equation: How People Treat Computers, Television, and New Media Like Real People and Places.* 3rd ed. Cambridge, UK: Cambridge University Press.
Reinganum, J. F., and L. L. Wilde. 1986. Equilibrium verification and reporting policies in a model of tax compliance. *International Economic Review* 27 (3): 739–760.
Remus, W. 1986. Graduate students as surrogates for managers in experiments on business decision making. *Journal of Business Research* 14 (1): 19–25.
Richards, P., and Tittle, C. R. 1981. Gender and perceived chances of arrest. *Social Forces* 59: 1182–1199.
Rilling, J. K., D. A. Gutman, T. R. Zeh, G. Pagnoni, G. S. Berns, and C. D. Kilts. 2002. A neural basis for social cooperation. *Neuron* 35 (2): 395–405.
Sally, D., and E. Hill. 2006. The development of interpersonal strategy: Autism, theory-of-mind, cooperation, and fairness. *Journal of Economic Psychology* 27(1): 73-97.
Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E., and Cohen, J. D. 2003. The neural basis of economic decision-making in the ultimatum game. *Science* 300(5626): 1755-1758.
Sansing, R. C. 1993. Information acquisition in a tax compliance game. *The Accounting Review* 68(4): 874–884.
Santoro, A., and C. Fiorio. 2011. Taxpayer behavior when audit rules are known: evidence from Italy. *Public Finance Review* 39 (1): 103-123.
Scholz, J. T., and N. Pinney. 1995. Duty, fear, and tax compliance: The heuristic basis of citizenship behavior. *American Journal of Political Science* 39(2):490-512.
Schwartz, R. D., and Orleans, S. 1967. On legal sanctions. *The University of Chicago Law Review 34*(2): 274-300.
Smith, K. W. 1992. Reciprocity and fairness: Positive incentives for tax compliance. In J. Slemrod (Ed.), *Why people pay taxes: Tax compliance and enforcement* Ann Arbor, MI: University of Michigan Press: 223–250.
Snow, A., and R. S. Warren. Jr. 2005. Ambiguity about audit probability, tax compliance, and taxpayer welfare. *Economic Inquiry* 43: 865–871.
Spicer, M. W., and Becker, L. A. 1980. Fiscal inequity and tax evasion: An experimental approach. *National Tax Journal* 33: 171–175.
Spicer, M. W., and Hero, R. E. 1985. Tax evasion and heuristics: A research note. *Journal of Public Economics* 26: 263–267.

Spicer, M. W., and J. E. Thomas. 1982. Audit probabilities and the tax evasion decision: An experimental approach. *Journal of Economic Psychology* 2(3): 241–245.
Srinivasan, T. N. 1973. Tax evasion: A model. *Journal of Public Economics* 2 (4): 339–346.
Tan, F., and A. Yim. 2014. Can strategic uncertainty help deter tax evasion? An experiment on auditing rules. *Journal of Economic Psychology* 40: 161–174.
Torgler, B., and Schneider, F. 2004. Does culture influence tax morale? Evidence from different European countries. *CREMA Working paper.* No. 2004-17.
Torgler, B., and Valev, N. T. 2006. Women and illegal activities: Gender differences and women's willingness to comply over time. *Andrew Young School of Policy Studies Research Paper* (06-56).
Traeger, M. L., S. S. Sebo, M. Jung, B. Scassellati, and N. A. Christakis. 2020. Vulnerable robots positively shape human conversational dynamics in a human–robot team. *Proceedings of the National Academy of Sciences*117(12): 6370-6375.
Trivedi, V. U., and J. O. Y. Chung. 2006. The impact of compensation level and context on income reporting behavior in the laboratory. *Behavioral Research in Accounting* 18: 167–183.
Unger, R. K. 1979. Toward a redefinition of sex and gender. *American Psychologist* 34: 1085–1094.
Van Lange, P. A., De Bruin, E., Otten, W., and Joireman, J. A. 1997. Development of prosocial, individualistic, and competitive orientations: theory and preliminary evidence. *Journal of personality and social psychology 73*(4): 733.
Vogel, J. 1974. Taxation and public opinion in Sweden: An interpretation of recent survey data. *National Tax Journal* 27: 499–513.
Ward, E. 1993. Generalizability of psychological research from undergraduates to employed adults. *The Journal of Social Psychology* 133 (4): 513–519.
Wenzel, M. 2002. The impact of outcome orientation and justice concerns on tax compliance. The role of taxpayers' identity. *Journal of Applied Psychology* 87: 629–645.
Wilson, J., and Sheffrin, S. 2005. Understanding surveys of taxpayer honesty. *Finanzarchiv* 61: 256–274.
Yitzhaki, S. 1974. Income tax evasion: A theoretical analysis. *Journal of Public Economics* 3 (2): 201–202.

Appendix A. Derivation of equilibrium

The game comprises a risk-neutral taxpayer and a similarly risk-neutral tax auditor.[25] Most studies on tax evasion do not differentiate either with respect to the kind of tax, that is, whether it is individual, corporate, or value-added tax, or with respect to the person or organization evading the tax. Although a kind of income taxation seems to be assumed implicitly, as pointed out by Alm (2012), tax evasion and avoidance is similarly possible with other taxes too. Thus, we consider our research results to be relevant for other taxes.

The taxpayer's true income is private information that cannot be observed by the tax auditor. Based on true income, the taxpayer reports the taxable income to the tax auditor. As the tax auditor does not know the true income, he/she estimates it from the reported income and decides on an effort level to engage in the tax audit. The auditor's effort level determines the verification probability of the true income through the tax audit; the higher the effort level of tax audit, the greater the probability that the true income will be verified.

The taxpayer's true income, I, is a random variable with a range of $I \in [\underline{I}, \overline{I}] (\underline{I} < \overline{I} < \infty)$ and a distribution function $F(\cdot)$.[26] In the game, after the taxpayer observes his/her true income, he/she reports a taxable income of $x = r(I)$. If the taxpayer is not audited, he/she pays tax of tx based on a proportionate tax rate of t. If the taxpayer is audited and the true income is verified, the tax is levied on the true income; in addition, the taxpayer is subject to a fixed penalty according to the difference between the true and reported incomes. Therefore, the amount paid by the taxpayer in this instance becomes $tI + t\pi(I - x)$, where π is a penalty rate for tax evasion. According to Yitzhaki (1974), the assumption about the penalty is considered to conform to the tax laws of the United States. Furthermore, this form of penalty is valid for many other

[25] The preference for risk has an impact on equilibrium values. Therefore, when we compare analytical and experimental results, we attempt to control the subjects' risk preferences by giving them spreadsheets as a benchmark for calculating risk-neutral payoff.

[26] Although Reinganum and Wilde (1986) do not specify the distribution form, for simplicity, we assume that true income is uniformly distributed between $\underline{I}$ and $\overline{I}$.

countries.

After observing the taxpayer's reported income, x, the auditor chooses the audit effort level. The effort of tax audit entails costs, and in reality, even if the taxpayer's under-reporting is verified, it is assumed that these costs are still incurred. In other words, for example, even for a case involving reported income below $\underline{I}$, which clearly represents a case of under-reporting, if the tax auditing costs are high enough, it is possible that auditing effort is not exerted. The tax auditor makes a costly effort set as ρ to verify true income, which corresponds to the verification probability, $p(x)$. Therefore, the auditor's strategy is expressed as $\rho = p(x)$, $p: (-\infty, \infty) \rightarrow [0, 1]$. In this formulation, the verification probability is unrelated to the degree of under-reporting. In addition, this assumes that the audit verification does not partly reveal the true income, but results only in success or failure. For simplicity, the audit cost is assumed to be linear in the audit effort, so that $c\rho$, where c is the marginal cost of exerting effort. The audit cost is considered to be an increasing function of audit effort level.[27]

The tax auditor's utility function, U_A, is expressed as follows:

$$U_A = \rho\big(tE[I|x] + \pi t(E[I|x] - x)\big) + (1 - \rho)tx - c\rho, \quad (1)$$

where $E[I|x]$ is the auditor's estimated value of the true income, based on his/her observation of the reported income. The first term in equation (1) is the tax auditor's payoff when the tax audit is executed, which consists of tax revenue based on the true income and penalty. The second term is the tax auditor's payoff when the audit is not executed, which consists of the reported income. The third term is the tax auditor's effort cost, which depends on the audit effort level, and is incurred regardless of whether the taxpayer is actually audited.

[27] As mentioned in Reinganum and Wilde (1986), the cost function, $c\ (\rho)$, is twice continuously differentiable for ρ and satisfies the following restrictions: $0 < c'(\rho) < \infty$ and $0 < c''(\rho) < \infty$, $\lim_{p\rightarrow 1} c'(\rho) = \infty$, $c'\ (\rho)/c''\ (\rho)\ + \rho > 1/(1 + \pi)$. In the case of a linear cost function, one part of this condition is not satisfied, but there exists a unique equilibrium solution.

The taxpayer's expected utility function, U_P, is expressed as follows:

$$U_P = p(x)(I - tI - \pi t(I - x)) + \big(1 - p(x)\big)(I - tx) \qquad (2)$$

The first term in equation (2) is the taxpayer's payoff when he/she is audited and the second term is that when he/she is not audited.

The timing of events is as follows: (1) observing true income *I* as private information, the taxpayer reports taxable income *x* that maximizes U_P; (2) estimating true income from the reported income, the tax auditor chooses the audit effort level that maximizes U_A; and (3) in equilibrium, the estimate of true income $E[I|x]$ is equal to the true income *I*.

Solving the problems using backward induction, we derive the following equilibrium conditions.

i. The equilibrium audit probability is as follows:

$$p(x) = \begin{cases} 0, & x \geq \bar{x} \\ \dfrac{1}{1+\pi}\left(1 - \exp\left\{\frac{-t(1+\pi)}{c}(\bar{x} - x)\right\}\right), & x \in [\underline{x}, \bar{x}] \\ 1, & x < \underline{x} \end{cases}$$

ii. The equilibrium reported income is as follows:

$$x = I - \frac{c}{t(1+\pi)}, I \in \left[\underline{I}, \bar{I}\right]$$

iii. The auditor's equilibrium conjectured income is as follows:

$$E[I|x] = \begin{cases} \bar{I}, & x \geq \bar{x} \\ x = I - c/t(1+\pi), & x \in [\underline{x}, \bar{x}] \\ \underline{I}, & x < \underline{x} \end{cases}$$

The interpretation of this equilibrium can be described as follows. First, from the reported income in equilibrium condition (ii), we find that the taxpayer whose true income is *I* reports smaller than *I* in the equilibrium. This is because the taxpayer takes the costly tax audit into consideration. This reported income increases with true income, the tax rate, and the penalty rate, and decreases with the marginal audit cost *c*.[28]

Next, we examine the audit (verification) probability in equilibrium. The equilibrium audit probability from equilibrium condition (i) is 0 when the reported income exceeds its upper limit, 1 when the reported income is below its lower limit, and between 0 and 1 when the reported income is in between. In the region of reported income between 0 and 1, the equilibrium audit probability is convex with respect to the reported income. In other words, if the reported income is higher, the marginal probability change is also higher. The intuitive explanation of this characteristic is as follows. When the taxpayer evades tax payment under a relatively low income, he/she incurs more evasion costs because the tax evasion is easily verified in this case owing to high audit probability. Therefore, the taxpayer's benefit from tax evasion is lower under a relatively low compared to a relatively high income. As a result, the tax auditor does not have an incentive to increase the effort level to verify the tax evasion for low reported income.

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[28] In this model, a degree of tax evasion does not depend on the true income. This result comes from the assumption that the audit cost function is linear in the audit effort level.

Appendix B. Descriptive statistics, Pearson's correlation coefficient, and the definition of variables in regressions

The descriptive statistics, Pearson correlations of our experimental data, and the definition of variables are summarized in Tables B1, B2, and B3.

(Insert Tables B1 – B3 about here.)

Appendix C. Instruction used for the experiment[29]

1. Roles

The following decision-making problem requires two roles: the Taxpayer and the Tax auditor. *Your role in this game will be randomly determined by the computer at the start of the game (your role is the Taxpayer, and the computer acts as the Tax auditor)*, and will remain unchanged until the end of the game.

2. Rules for decision-making

At the start of the game, pairs consisting of a Taxpayer and a Tax auditor are formed. *The combination of pairs is determined randomly by the computer and changes each time*. Decisions are made by each pair. The timeline of the game is as follows.

The timeline

Stage 1: Observing true income (Taxpayer only)

Stage 2: Taxpayer's decision-making

Stage 3: Tax auditor's decision-making

Stage 4: Results.

Stage 1: Observing true income (Taxpayer only)

First, the Taxpayer observes "true income," which is determined randomly as an integer in increments of 1 million from 5 million to 10 million (={500, 600, 700, 800, 900, 1000}). Also, a Taxpayer can observe "true income," but a Tax auditor cannot observe it.

Stage 2: Taxpayer's decision

[29] The underlined text in italics varies depending on the conditions (the computer condition appears within parentheses).

The Taxpayer decides the level of reported income (= {0, 100, 200, 300, 400, 500, 600, 700, 800, 900, 1000}) after the Taxpayer observes his/her true income.

The Taxpayer also answers "Yes" or "No" to the expectation of "whether or not you think the auditor conducts the tax investigation" for your reported income. This expectation will not be conveyed to the Tax auditor, and it has nothing to do with whether or not an actual survey has been conducted. The time limit for this decision is 30 seconds.

Stage 3: Tax auditor's decision

The Tax auditor chooses the probability of tax audit after they observe the reported income. The probabilities are 0–100%, in 1% increments. In addition, in order to conduct the audit, the verification cost described later will be required. The time limit for this decision is 30 seconds.

Also, for Taxpayer and Tax auditor, the "recommended audit probability" list based on certain calculations is shown in the attachment. Please make a decision based on the value.

Stage 4: Results

After Stage 3, the computer decides whether to audit depending on the verification probability.

If the Taxpayer is audited and the true income is verified, the tax is levied on the true income; in addition, the Taxpayer is subject to a fixed penalty according to the difference between the Taxpayer's true and reported incomes. If the Taxpayer is not audited, the Taxpayer pays tax based on a proportionate tax rate. The tax rate is 0.4, and the penalty is 1.5.

Points earned by the Taxpayer when he/she is audited

= (true income) − (true income × tax rate) – [(true income − reported income) × tax rate × 1.5]

Points earned by the Taxpayer when he/she is not audited

= (true income) − (reported income × tax rate)

Points earned by the Tax auditor when the Taxpayer is audited

= (true income × tax rate) + [(true income − reported income) × tax rate × 1.5] − (audit costs)

Points earned by the Tax auditor when the Taxpayer is not audited

= (reported income × tax rate) – (audit costs)

The audit costs incurred by the Tax auditor are as follows:

・No audit, 0

・If the auditor conducts a tax audit, 200.

3. Repeated decision-making

Repeat the decision sequence described above 20 times. *The Taxpayer and the Tax auditor pairs are randomly determined each time, so you do not make repeated decisions with any particular partner.*

Appendix D. Recommended audit probability list

Reported income	Recommended audit probability
1000 900 800	0%
700	16%
600	25%
500	31%
400	35%
300	37%
200 100 0	100%

Notes: We distributed a "recommended audit probability" list to all participants (taxpayers under the computer condition, and both taxpayers and tax auditors under the human condition) as a decision aid. This is a table listing the equilibrium probabilities of audit for reported incomes to control the influence of the probability of audit between two conditions. In our experiments, under the computer condition, the participants in the taxpayer role are told that the auditor is a "computer" that follows rules based on this list. Under the human condition, all participants (both taxpayers and tax auditors) are told that they may use this list, which is based on certain calculations, as a reference for determining (or estimating) the probability of an audit.

Appendix E. Analysis of the taxpayer's risk perception of tax audit by condition

In this appendix, we analyze the taxpayer's risk perception of tax audit under both conditions. In the experiments, we also asked the taxpayer the audit expectation, "do you think you will be tax audited? (Yes/No)" when determining reported income (the answer is "yes," then the index is equal to "1," if not, the index is "0"). The taxpayer estimates the risk of tax audit when observing true income and determining reported income. Table C1 shows the rate of the taxpayers' risk perception of tax audit by condition.

[Insert Table C1 about here.]

The difference in compliance rate between the two conditions can be explained by the difference in the risk perception of tax audit when determining reported income. Panel A of Table C1 depicts the rate of the taxpayers' risk perception of tax audit by condition and gender/SVO. The rate of taxpayers' risk perception of tax audit is defined as the percentage of taxpayers answering "yes." Panel A of Table C1 indicates that all levels of the rate of taxpayers' risk perception of tax audit under the human condition were higher than those under the computer condition (Fisher's exact test). Panel B of Table C1 indicates that, when controlling for compliance rate, all levels of the rate of taxpayers' risk perception of tax audit were higher under the human condition compared to the computer condition (Fisher's exact test, $p < 0.01$ when $0.2 \leq$ compliance rate ≤ 1). This result implies that since the taxpayer under the human condition recognizes the risk of tax audit higher, the taxpayer under the human condition becomes more compliant.

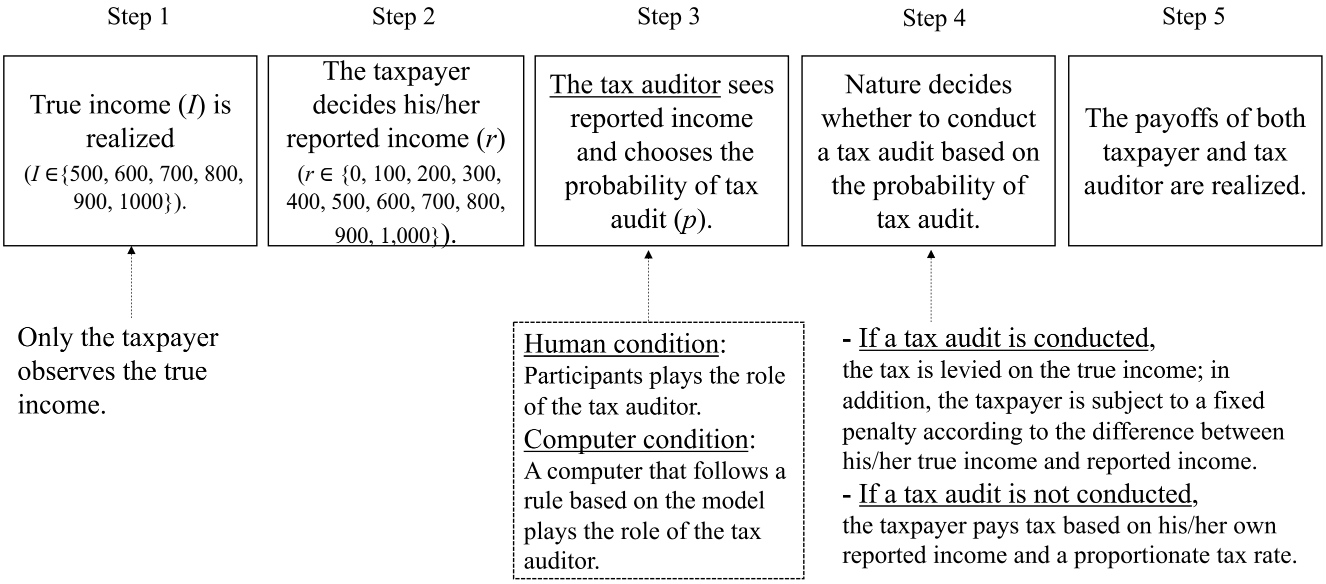
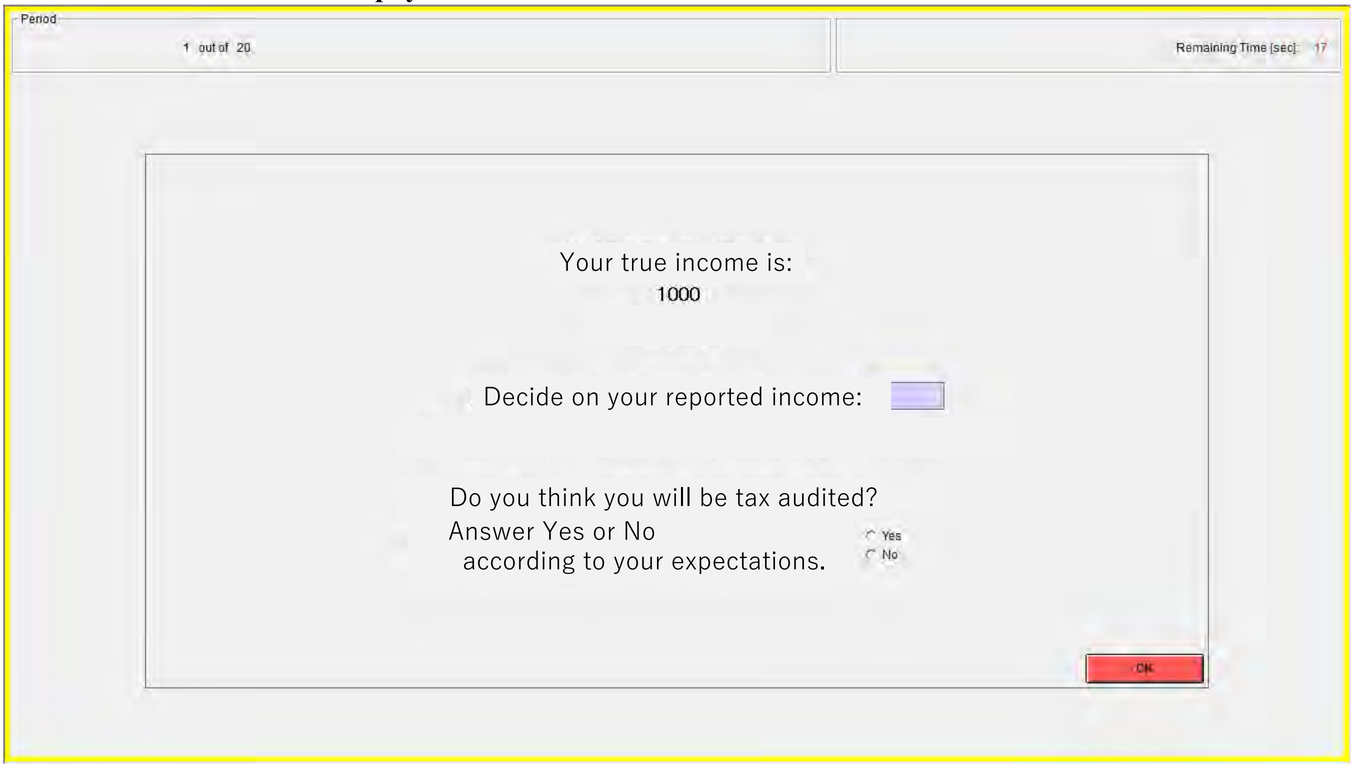


Figure 1. The timeline of the tax compliance game

Notes: This figure illustrates the timeline of the tax compliance game. We adopted a 2×1 experimental design, in which the type of the tax auditor was manipulated between participants at two levels: computer and human auditor conditions. In step 1, true income (I) is realized ($I \in \{500, 600, 700, 800, 900, 1000\}$). Only the taxpayer observes the true income. In step 2, The taxpayer decides his/her reported income (r) ($r \in \{0, 100, 200, 300, 400, 500, 600, 700, 800, 900, 1000\}$). In step 3, the tax auditor sees reported income, and chooses the probability of tax audit (p). Under the human condition, participants play the role of the tax auditor. Under the computer condition, a computer that follows a rule based on the model plays the role of the tax auditor. In step 4, nature decides whether to conduct a tax audit based on the probability of tax audit. If a tax audit is conducted, the tax is levied on the true income; in addition, the taxpayer is subject to a fixed penalty according to the difference between his/her true and reported incomes. If a tax audit is not conducted, the taxpayer pays tax based on his/her own reported income and a proportionate tax rate. In step 5, the payoffs of both taxpayer and tax auditor are realized. After step 5, taxpayers and tax auditors are randomly re-matched and, thereafter, steps 1–5 are repeated for a total of 20 rounds.

Panel A. The screen of the taxpayer's decision



Panel B. The screen of the tax auditor's decision

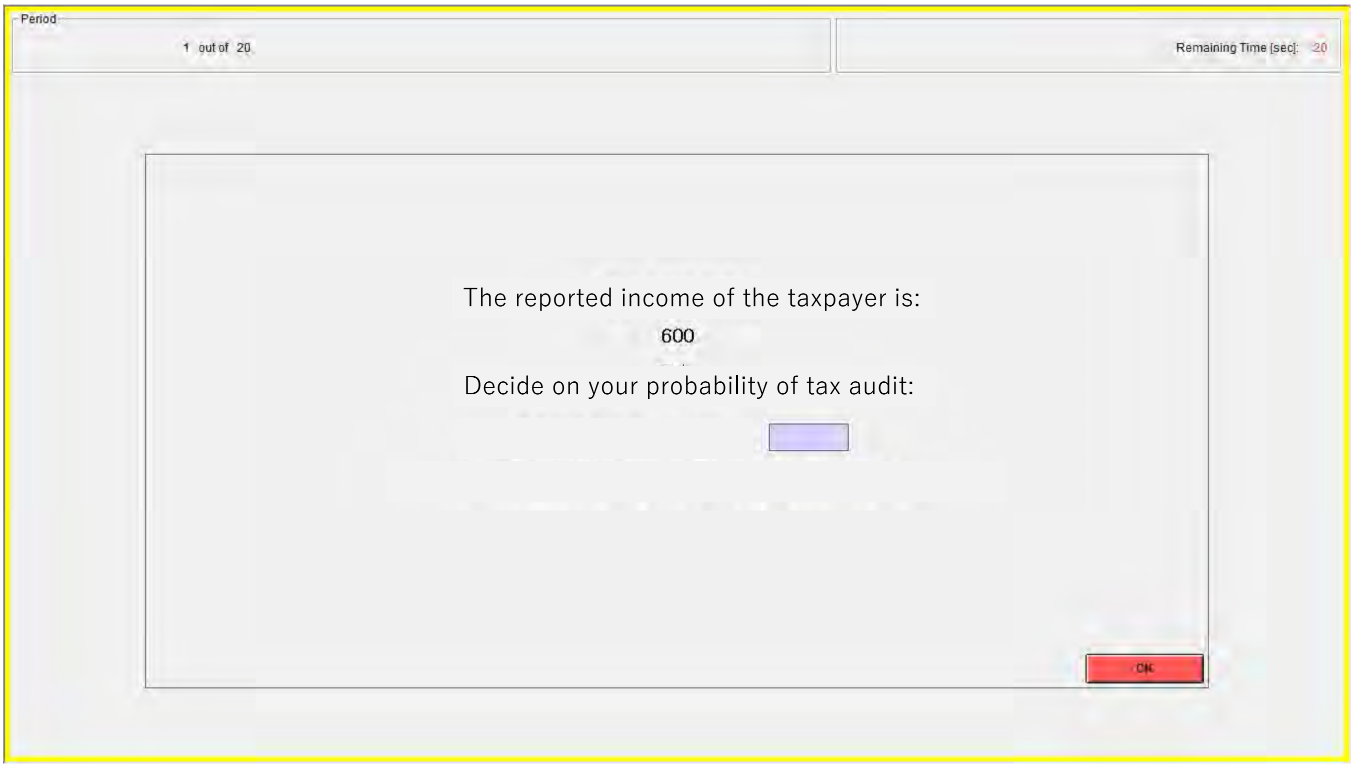


Figure 2. The screens of the experiment

Notes: This figure shows the screens of the experiment: Panel A, for the taxpayer's decision; and Panel B, for the tax auditor's decision, respectively.

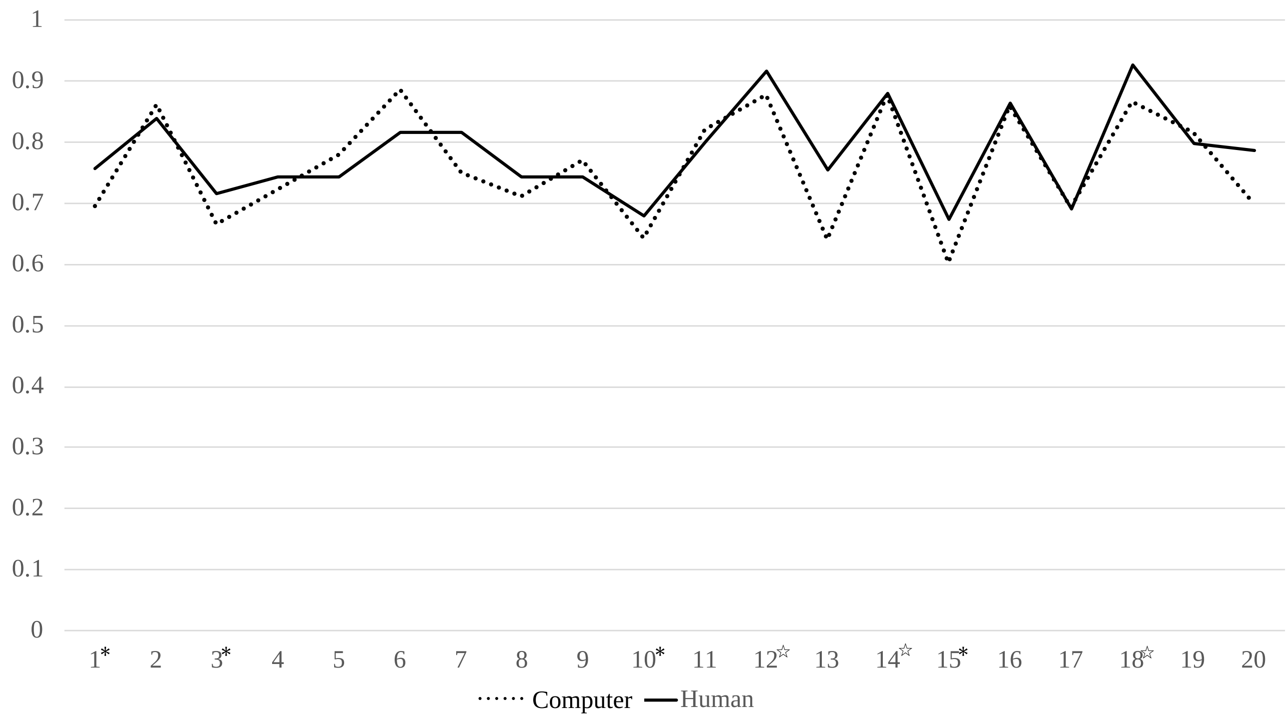


Figure 3. Mean levels of the compliance rate for each condition by period

Note: This figure shows the average levels of the compliance rate for each condition by period. We adopted a 2×1 experimental design, in which the type of auditor was manipulated between participants at two levels: computer and human auditor conditions. Asterisks are appended to the upper right corner of the rounds in which the true income is equal to 1,000 (maximum). Stars are appended to the upper right corner of the rounds in which the true income is equal to 500 (minimum).

Table 1. Numerical example of equilibrium

True income	Reported income	Probability of tax audit	Expected payoff for taxpayers	Expected payoff for auditors
1000	800	0	680	320
900	700	0.16	588.52	280
800	600	0.25	509.43	240
700	500	0.31	437.85	200
600	400	0.35	370.82	160
500	300	0.37	306.56	120

Notes: this table presents the numerical example of equilibrium. We use this example for our experiment. Please also see Figure 1 for the timeline of the game.

Table 2. Experimental design

C	Participants	T	A	Rounds	T-obs.	A-obs.
Human	76	38	38	20	760	760
Computer	40	40	-	20	800	800
Total	116	78	38		1560	1560

Notes: this table presents the experimental design. The items in this table are as follows: condition (C), number of participants, taxpayers (T), auditors (A), rounds, and total number of observations for taxpayers (T-obs.) and auditors (A-obs.) in the experiment.

Table 3. Descriptive statistics of the compliance rate of taxpayers for each experimental condition

Panel A. Compliance rate of taxpayers by condition and gender

		Condition	
		Computer	Human
All	Mean	0.761	0.781
	S.D.	0.199	0.197
	Obs.	800	760
Male	Mean	0.723	0.791
	S.D.	0.223	0.198
	Obs.	350	340
Female	Mean	0.791	0.774
	S.D.	0.172	0.196
	Obs.	450	420

Panel B. Compliance rate of taxpayers by condition and individual prosociality

		Condition	
		Computer	Human
Prosocial type	Mean	0.776	0.845
	S.D.	0.168	0.167
	Obs.	320	140
Other type	Mean	0.751	0.767
(Individualistic	S.D.	0.216	0.200
and competitive)	Obs.	480	620

Notes: Tables report the descriptive statistics of the compliance rate of taxpayers by each experimental condition. Panel A presents the compliance rate by condition and gender and Panel B shows the compliance rate by condition and individual prosociality. *S.D.* means standard deviation and *Obs.* means the number of observation.

Table 4. The results of regressions

	Dependent variable: tax compliance rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent variables						
PCD	−0.0414***	−0.0654***	−0.0990***	0.00761	−0.0145	−0.112***
	(−2.98)	(−3.21)	(−5.03)	(0.40)	(−0.90)	(−4.18)
$Audited_{t-1}$	0.121***	0.115***	0.0580	0.166***	0.133***	0.0625
	(4.69)	(4.54)	(1.65)	(4.96)	(4.26)	(1.46)
$Fine_{t-1}$	−0.151***	−0.144***	−0.105***	−0.185***	−0.174***	−0.0574
	(−5.44)	(−5.29)	(−2.69)	(−5.16)	(−5.17)	(−1.27)
Ln (TI)	−0.540***	−0.538***	−0.738***	−0.393***	−0.581***	−0.437***
	(−17.46)	(−17.50)	(−15.52)	(−10.08)	(−15.03)	(−9.17)
GEN	0.0216	−0.0229			0.0427**	−0.0123
	(1.55)	(−1.16)			(2.49)	(−0.52)
PRO	0.0475***	0.114***	0.0984***	0.00752		
	(3.31)	(4.38)	(4.50)	(0.41)		
Dark	0.000955	0.00120	−0.00171	0.00411**	0.00119	0.00224
	(0.92)	(1.18)	(−1.35)	(2.38)	(0.88)	(1.51)
MFQ	−0.00126***	−0.00112**	−0.00164**	−0.000604	−0.00108*	−0.00156***
	(−2.77)	(−2.46)	(−2.42)	(−1.00)	(−1.66)	(−2.67)
TD	−0.00419***	−0.00418***	−0.00464**	−0.00361**	−0.00325**	−0.00608***
	(−3.47)	(−3.51)	(−2.52)	(−2.37)	(−2.12)	(−3.37)
$GEN \times PCD$		0.0993***				
		(3.88)				
$PRO \times PCD$		−0.116***				
		(−3.74)				
Constant	4.518***	4.491***	5.995***	3.379***	4.733***	3.955***
	(20.69)	(20.75)	(17.90)	(12.32)	(17.14)	(12.00)
Sigma						
constant	0.234***	0.232***	0.229***	0.226***	0.243***	0.203***
	(42.99)	(42.93)	(29.16)	(31.56)	(38.56)	(20.42)
Observations	1482	1482	655	827	1045	437
Pseudo R^2						
F	37.942	34.520	37.817	15.357	30.943	14.980

Notes: Tobit model with limits at 0 and 1 for the dependent variable: the tax compliance rate as the ratio of reported true income. *t* statistics calculated using robust standard errors are in parentheses underneath coefficients. Significance levels: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table B1. Descriptive statistics of variables using regressions

Variables	Observations	Mean	Standard deviation	Min	Max
Comp	1482	0.77	0.20	0.00	1.00
PCD	1482	0.51	0.50	0.00	1.00
$Audited_{t-1}$	1482	0.30	0.46	0.00	1.00
$Fine_{t-1}$	1482	0.22	0.42	0.00	1.00
Ln (Income)	1482	6.60	0.23	6.21	6.91
GEN	1482	0.56	0.50	0.00	1.00
PRO	1482	0.29	0.46	0.00	1.00
Dark	1482	33.08	6.92	18.0	53.00
MFQ	1482	99.14	13.74	53.00	132.00
TD	1482	10.94	5.49	1.00	20.00

Table B2. Pearson correlation coefficients

	Comp	*PCD*	$GEN \times PCD$	$PRO \times PCD$	$Audited_{t-1}$	$Fine_{t-1}$	*Ln (TI)*	*GEN*	*PRO*	*Dark*	*MFQ*	*TD*
Comp	1.000											
PCD	−0.051	1.000										
$GEN \times PCD$	0.064	0.622	1.000									
$PRO \times PCD$	0.013	0.495	0.485	1.000								
$Audited_{t-1}$	−0.018	−0.136	−0.104	−0.086	1.000							
$Fine_{t-1}$	−0.066	−0.106	−0.077	−0.060	0.816	1.000						
Ln (TI)	−0.370	0.004	0.003	0.009	0.059	0.002	1.000					
GEN	0.066	0.011	0.567	0.167	−0.037	−0.006	0.000	1.000				
PRO	0.086	0.237	0.304	0.786	−0.041	−0.045	0.007	0.153	1.000			
Dark	−0.006	0.096	−0.118	0.035	−0.021	−0.030	0.003	−0.375	−0.085	1.000		
MFQ	−0.057	−0.150	−0.106	−0.084	−0.023	0.019	0.001	0.056	−0.058	0.070	1.000	
TD	0.056	−0.010	−0.004	−0.020	0.097	0.023	−0.358	0.002	−0.015	−0.012	−0.003	1.000

Table B3. Variable definitions

Variables	Definitions
Comp	The portion of income declared (ratio of declared to true income).
PCD	An indicator variable that is 1 if the experiment is under computer auditor condition and 0 if under human auditor condition.
$Audited_{t-1}$	An indicator variable that is 1 if the participant is audited in the previous round and 0 otherwise.
$Fine_{t-1}$	An indicator variable that is 1 if the participant is punished in the previous round and 0 otherwise.
Ln (TI)	The natural logarithm of the true income.
GEN	An indicator variable that is 1 if the participant is female and 0 if the subject is male.
PRO	An indicator variable that is 1 if the participant has prosocial tendencies according to the social value orientation, which is the measure of social preferences presented by Van Lange, Otten, De Bruin, and Joireman (1997), and 0 otherwise.
Dark	The total score of the Dark Triad Dirty Dozen measure of Jonason and Webster (2010), which consists three factors: narcissism, Machiavellianism, and psychopathy.
MFQ	The degree to which people prioritize five foundational domains in moral decision-making: Harm/Care, Fairness/Reciprocity, Ingroup/Loyalty, Authority/Respect, and Purity/Sanctity (Graham et al. 2011).
TD	Time dummies.

Table C1. The rate of taxpayers' risk perception of tax audit by condition

Panel A. The rate of taxpayers' risk perception of tax audit by condition, gender, and social value orientation

		Condition		
		Computer	Human	
All	Mean	0.246	0.353	***
	S.D.	0.431	0.478	
	Obs.	800	760	
Male	Mean	0.257	0.332	**
	S.D.	0.438	0.471	
	Obs.	349	340	
Female	Mean	0.237	0.371	***
	S.D.	0.425	0.483	
	Obs.	451	420	
Prosocial type	Mean	0.240	0.314	*
	S.D.	0.428	0.465	
	Obs.	320	140	
Other type	Mean	0.250	0.362	***
	S.D.	0.433	0.481	
	Obs.	480	620	

Panel B. The rate of taxpayers' risk perception of tax audit by condition and compliance rates

Compliance rate (CR)	Average true income		Rate of taxpayers' risk perception of tax audit		
	Computer	Human	Computer	Human	
0.8 < CR ≤ 1	683.96	688.59	0.2886	0.3742	***
			[343]	[342]	
0.6 < CR ≤ 0.8	824.60	838.60	0.1547	0.2573	***
			[252]	[272]	
0.4 < CR ≤ 0.6	806.66	794.05	0.2800	0.4455	***
			[150]	[101]	
0.2 < CR ≤ 0.4	905.55	830.76	0.3148	0.5897	***
			[54]	[39]	
0 ≤ CR ≤ 0.2	800.00	866.66	0.0000	0.5000	*n.s.*
			[1]	[6]	

Notes: table presents the rate of taxpayers' risk perception of tax audit. In the experiments, we also asked the taxpayer about their expectation of audit, "do you think you will be tax audited? (Yes/ No)" when determining reported income (if the answer is "yes," the index is equal to "1," if not, the index is "0"). The rate of taxpayers' risk perception of tax audit is defined as the percentage of taxpayers answering "yes."

Panel A shows the rate of taxpayers' risk perception of tax audit by condition, gender, and social value orientation. Panel B shows the rate of taxpayers' risk perception of tax audit by condition and compliance rate. Here, we use Fisher's exact test to statistically examine the equality of proportions: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, and *n.s.,* non-significant.