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Information processing in tax decisions: a MouselabWEB study on the deterrence model of income tax evasion

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Abstract

The highly influential Allingham and Sandmo model of income tax evasion assumes that taxpayers are driven by utility maximization, choosing evasion over compliance if it yields a higher expected profit. We test the main assumptions of this so-called deterrence approach considering both compliance decisions and the process of information acquisition using MouselabWEB. In an incentivized experiment, 109 participants made 24 compliance decisions with varying information presented for four within-subject factors (the four central model parameters: income, tax rate, audit probability, and fine level). Additionally, explicit expected value information was indicated in one of two conditions. The results reveal that participants attended to all relevant information, a prerequisite for expected value-like calculations. As predicted by the deterrence model, choices were clearly influenced by audit probability and fine level. Against the model assumptions, the presented parameters were not integrated adequately, indicated by a non-monotonic increase of evasion with rising expected rate of return from evasion. Additionally, more transitions between information necessary for calculating expected values did not result in higher model conformity, just as presenting explicit information on expected values. We conclude that deterrence information clearly influences tax compliance decisions in our setting but observed deviations from the deterrence model can be attributed to failures to properly integrate all relevant parameters.

KEYWORDS

deterrence, expected value, Mouselab, process tracing, rational choice, tax compliance

1 | INTRODUCTION

In the early 1970s, Allingham and Sandmo (1972) framed the decision whether to comply with tax laws or to evade taxes as a decision under uncertainty.[1] Their model of income tax evasion is rooted in the economics-of-crime paradigm (Becker, 1968). Accordingly, taxpayers are driven by utility maximization, choosing evasion over compliance if it yields a higher expected profit. The actual compliance decision depends on the individual income, the respective tax rate, the probability of being audited, and the severity of fines for evasion and is exclusively determined by the economic consequences of detection and punishment. In simple terms, this model assumes taxpayers to compare their net earnings after paying tax (considering income and tax rate) with the expected earnings from evading tax (taking audit probability and fine level into consideration), ultimately choosing the more attractive option.

The deterrence approach and especially the Allingham and Sandmo[2] model have served researchers mainly in the selection of independent variables to explain tax compliance, whereas for tax administrations, it has provided the foundation of enforcement-oriented policy paradigms. The model has been criticized for stripping tax decisions of any social context, yet it still can be considered the most influential model in tax research (for extensive discussions of the model and summaries of various extensions, see Alm, 2019; Andreoni et al., 1998).

From a behavioral perspective, the validity of the deterrence approach has been challenged because compliance rates in tax experiments are usually higher than predicted (Alm et al., 1992; Alm et al., 2010) and selected studies fail to find positive deterring effects of audits and fines (Iyer et al., 2010; Kirchler et al., 2010; Slemrod et al., 2001). Accordingly, deterrence-based models clearly overpredict noncompliance rates in the real world. Considering the relatively low probabilities of being audited for most taxpayers in combination with rather mild monetary fines for detected tax evasion, tax evasion should be omnipresent. This clearly is not the case (Alm, 2019; Alm et al., 1992; Andreoni et al., 1998). Additionally, the effects of income and tax rate are inconclusive, both from a theoretical and from an empirical perspective (see, for instance, Allingham & Sandmo, 1972; Alm & Malézieux, 2021; Kirchler et al., 2010; Yitzhaki, 1974). Concerning the relation of income and compliance, the Allingham and Sandmo model does not offer a clear prediction. With regard to tax rate, the Allingham and Sandmo model assumes two contrary effects: An increase in tax rate reduces the return of compliance (i.e., the substitution effect), but an increase in tax rate also decreases income, potentially leading to higher risk aversion, resulting in higher compliance (i.e., the income effect) (Allingham & Sandmo, 1972).

In light of observed deviations from the assumptions of the deterrence approach, the importance of considering further factors in explaining tax behavior has been stressed (e.g., Braithwaite, 2009; Kirchler, 2007; Kirchler et al., 2008; Torgler, 2002; Wenzel, 2004). Accordingly, taxpayers are no longer classified as rational utility maximizers but conceived as a heterogeneous group of people with differing beliefs and preferences also influenced by factors such as trust in governmental authorities, attitudes, social norms, and fairness considerations.

The present study takes a step back, focusing exclusively on the four factors explicitly considered in the deterrence approach. The main aim is to investigate whether implicit assumptions of the model concerning the cognitive processes underlying decision making are reflected in the acquisition of information in the lab.

1.1 | Expected values and expected utility

People can represent expected outcomes in uncertain situations in different ways. Applying expected utility maximization (von Neumann & Morgenstern, 1947), the Allingham and Sandmo (1972) model assumes diminishing marginal utility of income implying that individuals are risk averse. In contrast, an expected value approach assumes risk neutrality where values are represented linearly, and individuals are assumed to accept any risk if the long-term expected outcome is more attractive (cf. Srinivasan, 1973).

Irrespective of differences between the two concepts, both are based on the same key assumption: Rational decision makers behave as if they were attempting to maximize their expectations (Li, 2003). Importantly, both approaches are considered "as-if" models, as they claim that decision makers' choices are in line with calculations of an expectation, but not that they must actually make these calculations. In other words, these models address the decision outcomes rather than the process (Stewart et al., 2016). However, it has been shown that it is valuable to derive implicit and testable assumptions about the underlying decision process (see Orquin & Mueller Loose, 2013; Simon, 1955).

The most prominent assumption is that, when choosing between different options with uncertain consequences, decision makers must inevitably attend to all relevant information (Orquin & Mueller Loose, 2013). Furthermore, for each choice option, payoff and probability must be determined and multiplied to obtain the long-term payoff prospect for each option (i.e., the expected value). These prospects are then compared to each other, and then a final decision is made. Hence, transitions between provided information that is needed to identify the optimal choice option are necessary if we assume that individuals cannot integrate the information from working memory alone or use re-fixations to lower working memory demands (Orquin & Mueller Loose, 2013).

Predominantly studied in the context of gambles, expected value and expected utility approaches have achieved only limited success in explaining actual decision outcomes (e.g., Colbert et al., 2009; Li, 2003; Lichtenstein et al., 1969; Schulte-Mecklenbeck, Kühberger, et al., 2017; Su et al., 2013). There is evidence that a considerable share of people does not understand the concept of expected value and cannot apply it to decision problems (Lichtenstein et al., 1969). Even when expected values are explicitly presented and explained to participants, the option with the evidently higher expected value is not always chosen, especially in single-play situations (Li, 2003). Additionally, (implicit) assumptions of these rational choice models are challenged by studies investigating underlying cognitive processes. For instance, the observation of relatively short decision times challenges the assumption that individuals deliberately integrate probabilities and outcomes (Ayal & Hochman, 2009; Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011; Schulte-Mecklenbeck, Kühberger, et al., 2017).

1.2 | Tax compliance decisions

Although gambles and tax compliance decisions can be interpreted as structurally similar, there are also important differences: (1) While gambling studies relate to both the gain and the loss domain (e.g., Polezzi et al., 2010; Weller et al., 2010), taxpaying is focused on the loss domain. One option is a certain loss, that is, paying taxes, whereas the other option, that is, evasion, offers the chance to circumvent the loss in case of not being detected, with the risk of a possible audit resulting in a higher loss compared to being compliant. This differentiation is important, given that people are more prone to risky decisions when dealing with potential losses compared to making decisions in the domain of gains (e.g., Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). (2) Tax decisions are more complex than risky choice tasks, because in the tax context often additional factors like considerations of fairness (e.g., Kirchler, 2007) and social norms (e.g., Wenzel, 2004) play a role, which can, for instance, induce feelings of entitlement (Cullis et al., 2012). (3) Tax compliance decisions often provide more than two choice options, as partial evasion can be possible, which can result in higher decision difficulty. This is important because, for instance, a smaller difference in the expected value between gambles has been shown to affect the process of information acquisition (e.g., Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011; Schulte-Mecklenbeck, Kühberger, et al., 2017), presumably due to higher need of working memory capacity (Orquin & Mueller Loose, 2013). (4) Tax decisions entail an ethical component, and ethical and moral considerations influence tax behavior (Alm & Torgler, 2006; Torgler, 2002). Even in lab studies, participants are usually aware that compliance is the normatively expected behavior (e.g., Bruttel & Friehe, 2014). Altogether, we believe it is unclear how informative gambling studies are for the specific context of tax compliance decisions.

1.3 | The potential of investigating information processing in economic decision making

While the significance of process data in developing and testing theories is widely acknowledged in other areas of judgment and decision making (Johnson et al., 2008; Payne & Venkatraman, 2011; Schulte-Mecklenbeck, Johnson, et al., 2017; Schulte-Mecklenbeck et al., 2019), experimental research on tax behavior has focused on actual choices usually neglecting underlying cognitive processes. With some notable exceptions where arousal or emotions and their influence on the decision process have been explored (e.g., Coricelli et al., 2010; Dulleck et al., 2016; Enachescu et al., 2019), investigations of information processing are missing in tax research, despite the potential benefits for modeling tax behavior and the possibility of a better understanding of heterogeneity among individuals (Willemsen & Johnson, 2019).

There are two basic assumptions underlying the interpretation of visual information acquisition about the relationship between search and cognition that can be empirically tested (Costa-Gomes et al., 2001). First, *Occurrence* states that if information is used by a decision maker, it must have been acquired. Second, *Adjacency* assumes that information acquisition is temporally proximal to information use (see also Willemsen & Johnson, 2019).

MouselabWEB (Willemsen & Johnson, 2019) is a tool to monitor mouse cursor movements that allows to analyze the content, amount, and sequence of the information acquisition process. A decision maker has to deliberately open visually covered cells (boxes) of an information matrix displayed on a computer screen to access the underlying information. Each box has a label that indicates what particular information can be found in the box, and time data on box openings and closings is recorded. Compared to eye-tracking, which also captures more automatic and intuitive acquisitions, MouselabWEB is associated with more deliberate and controlled information acquisition, since information search is more costly as it requires active mouse cursor movement. Accordingly, these two techniques allow to analyze different aspects of information processing (see Norman & Schulte-Mecklenbeck, 2009). To investigate the assumed deliberate decision-making process of the deterrence approach, MouselabWEB can be considered as the more applicable method (e.g., Glöckner & Herbold, 2011; Lohse & Johnson, 1996; Norman & Schulte-Mecklenbeck, 2009).

Concerning the assumption that people's tax compliance decisions are based on maximizing their expectations, the analysis of the actual decision alone does not yield sufficient evidence for a decision process being in line with the deterrence approach. The combination of actual choices with process data allows us to observe whether people actually acquire the necessary information to perform expected value-like calculations and relate information acquisition patterns reflecting expected value calculations to their compliance choices.

1.4 | Research questions

Based on the related literature the present study investigates (1) to what extent participants' compliance decisions are in line with the predictions of the deterrence approach. We analyze whether expected deterring effects of audit probability and fine level are observed and whether individuals consistently evade more taxes with increasing expected rate of return from evasion. Besides the effects of audit probability and fine level, that are at the core of the Allingham and Sandmo (1972) model, we also investigate the influence of income and tax rate on tax compliance. Given the unclear relation between income and tax compliance from a theoretical perspective, we investigate the effect of income in our study but refrain from an explicit prediction. As in our experiment the imposed penalty is set on evaded taxes (and not evaded income), an increase in tax rate can be expected to lead to more tax compliance, as the substitution effect disappears and the income effect remains (see Yitzhaki, 1974). Additionally, we examine (2) whether participants acquire all relevant information provided to calculate expected values. If participants do not acquire all relevant information, they cannot form expectations in the first place, which would offer a simple explanation for observed deviations from the predictions of the deterrence approach. Even stronger evidence against the assumptions of the deterrence model, however, would be if individuals do pay attention to crucial information, but they do not consider it adequately. As a directly related next step, we test (3) whether decisions are more in line with the predictions of deterrence models when people exhibit (more) transitions between information assumed to be prerequisites of expected value-like calculations. Furthermore, we investigate (4) whether choices are more in line with the predictions of the deterrence approach when we provide explicit information about expected values of the choice options (i.e., expected value of evasion and sure outcome of compliance) so that own calculations are not necessary. If we would observe decisions that are more in line with the model's assumptions in this condition, then this could be an indication that people actually would decide as the deterrence approach assumes, but have difficulties to determine expected values, for instance, due to cognitive capacity limitations. Finally, we explore information acquisition by analyzing frequency, duration, and sequence of information acquisition and analyze how these measures relate to compliance decisions.

2 | METHOD

2.1 | Participants

Overall, 109 students (61 female) with a mean age of 27.23 years ($SD = 8.64$) participated in the experiment. Based on a priori consideration of statistical power ($\alpha = .05$, $1 - \beta = .80$, and an expected effect size of $d = 0.50$) a sample size of approx. $N = 100$ was targeted (Faul et al., 2007).[3] All participants were students at the University of Vienna, enrolled in social and natural sciences disciplines. Decisions in the experiment were incentivized, and participants were not deceived in any way.

2.2 | Design and procedure

A repeated measures design with the dependent variable tax compliance (dichotomous choice; full evasion of tax due vs. full compliance) was implemented. There were four within-subject factors which were fully permuted, resulting in 24 rounds: income (1000 vs. 3000 experimental currency units [ECU]), tax rate (30% vs. 50%), audit probability (10% vs. 25% vs. 40%), and fine level (paying back the evaded amount plus a fine of 100% vs. paying back the evaded amount plus a fine of 300%). The order of presentation of the 24 rounds was randomly determined beforehand. To control for a potential order effect, approx. half of the participants faced the 24 rounds in reverse order (starting with Round 24 and ending with Round 1).

There was one between-subject factor manipulating the presence or absence of explicit expected value information (No Expected Value Condition vs. Expected Value Condition). In the Expected Value Condition, for each decision, the sure outcome in case of compliance and the expected value of evasion were additionally presented. To be able to indicate one single explicit expected value for the evasion option in the respective condition, the design feature with the dichotomous choice variable was necessary. This feature is in line with a recent meta-study including 70 tax evasion experiments confirming a general tendency toward all-or-none behavior, with the two extremes as the clear modes (Alm & Malézieux, 2021). Other studies in tax research have also applied such a dichotomous choice design (e.g., Bayer & Sutter, 2009; Lefebvre et al., 2015; Lohse & Qari, 2014; Tan & Yim, 2014).[4] Additionally, participants in the Expected Value Condition were provided with an explanation of the concept of expected value before the experimental task (see Supporting Information).

Based on the levels of the within-subject factors, the 24 rounds can be classified into three categories with regard to the difference between the sure outcome of compliance and the expected value of the evasion option. In four rounds the sure outcome of compliance was higher than the expected value of evasion (favoring compliance), in 16 rounds it was lower (favoring evasion), and in the remaining four rounds the sure outcome of compliance and the expected value of evasion were equal. Feedback on eventual audits and corresponding fines was provided only at the end of the experiment (after Round 24) to avoid audit-related sequence effects—for instance, bomb crater effects (see Guala & Mittone, 2005; Mittone, 2006)—to interfere with our experimental manipulations, a strategy also applied in other tax experiments (e.g., Casal et al., 2016; Pántya et al., 2016). Participants were informed that the occurrence of audits was randomly determined based on the communicated audit probability in each round, just as the corresponding fines in case of detected evasion were the fine levels announced for the respective round.

We communicated that at the end of the session one of the 24 rounds would be randomly drawn and the remuneration depended on the payoff in this respective round (exchange rate of 250 ECU = 1 euro; in addition to a show-up fee of 2 euro).[5] The experiment took 20–25 min, and the mean payoff was 7.20 euro ($SD = 3.30$; $min = 2.00$, $max = 14.00$).

MouselabWEB (Willemsen & Johnson, 2019) was applied to monitor the frequency, duration, and sequence of information acquisition. In each round, information on income (e.g., "1000 ECU"), tax rate (e.g., "30%"), audit probability (e.g., "10%"), and fine level (e.g., "600 ECU") was hidden in labeled boxes and only available to participants when they opened the respective box by moving the mouse cursor over it (see Figure 1 for a schematic illustration). In the Expected Value Condition, the sure outcome in case of compliance (e.g., "700 ECU") and the expected value of evasion (e.g., "940 ECU") were additionally presented. When the mouse cursor was moved outside of the box, information disappeared again. In between rounds, a fixation cross (50 × 50 px) was presented for one second in the center of the screen. Presentation order of the four tax-related information boxes in both conditions (income, tax rate, audit probability, and fine level) was counterbalanced horizontally and vertically between participants to control for possible position effects. In addition, the compliance choice option positions were horizontally varied between participants.

The post-experimental questionnaire consisted of a self-assessment item to measure general risk preference ("How would you personally describe yourself: are you generally rather risk-seeking or rather risk-avoiding?"; Likert-type scale from 1 = *not risk-seeking at all* to 10 = *very risk-seeking*) and an item where participants had to indicate how much of a monetary gain in a lottery (i.e., *100,000 euros*) they would risk in a gamble with a 50% chance to double the contribution and a 50% chance to lose half of it (six options; from *0* to *100,000 euro*). Both items were taken from the German Socio-Economic Panel and were found to be a reliable predictor of actual risky behavior (Dohmen et al., 2011). Furthermore, four items

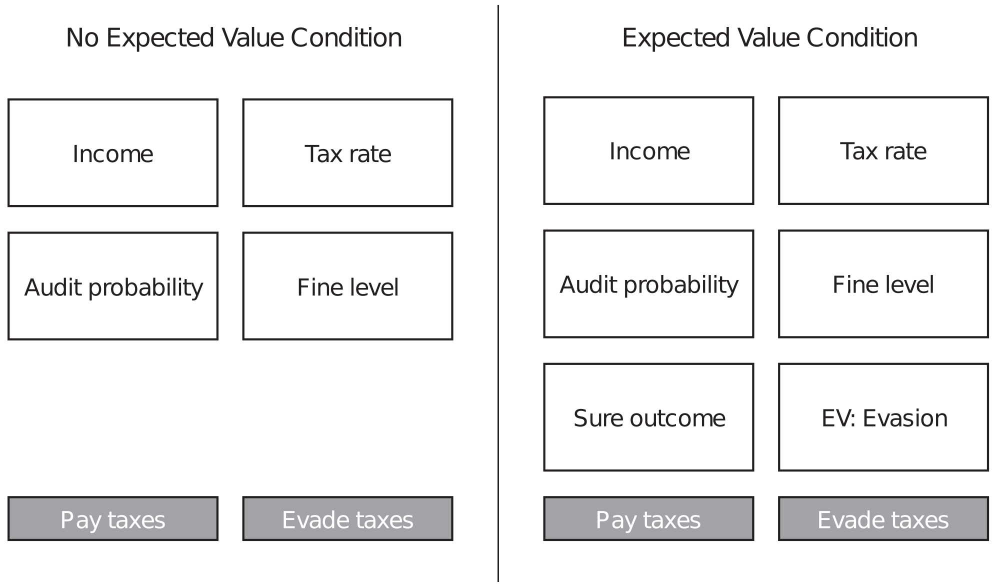

FIGURE 1 Schematic illustration of information presentation in the two experimental conditions. Note: In the expected value condition, sure outcome in case of full compliance and expected value of evasion were also presented. the presentation order of the boxes and the presentation order of the two choice options at the bottom was counterbalanced to control for order effects

measured whether participants based their decisions on expected values (e.g., "I made my choice according to expected values"; Likert-type scale from 1 = *not at all* to 7 = *very much*). Finally, understanding of the concept of expected value was assessed with an open question and four multiple-choice items (e.g., "The expected value is determined exclusively by the audit probability"; binary answer scale *not correct*/*correct*). For the complete questionnaire, see Supporting Information.

2.3 | Processing of MouselabWEB data

Information acquisition data were preprocessed with the *Datalyser* application included in MouselabWEB. As suggested by Payne et al. (1988), events with acquisition times under 100 ms were discarded, assuming that such short acquisitions cannot be processed consciously. In sum, the 109 participants made 2,616 decisions in the experiment, preceded by 18,312 box openings. For the process analysis, opening times were log-transformed to get a distribution of variables closer to a normal distribution, which is common practice (e.g., Schulte-Mecklenbeck et al., 2013).

2.4 | Open data accessibility

Data, codebook, and R code are publicly available via https://osf.io/h3ja6/.

3 | RESULTS

This section is divided into five subsections reflecting the structure of the research questions plus an additional section presenting results related to the post-experimental questionnaire.

3.1 | Conformity of choices with the deterrence approach

To assess to what extent compliance decisions were in line with the predictions of the deterrence model we used two approaches. First, we investigated whether decisions were influenced by the size of deterrence. More specifically, we tested whether increasing audit probabilities and fine levels were associated with higher compliance. Second, we inspected whether individuals' choices reflect stable preferences. One key assumption of the model is that evasion should be more prevalent as it becomes financially more attractive. Therefore, we should observe a stable increase of evasion with increasing expected return from evasion relative to compliance. Here we focus only on the No Expected Value condition, in which individuals were only presented with the four tax-related parameters.

To test which factors influenced compliance decisions in the No Expected Value Condition ($N = 53$), a mixed-effects model with compliance (binary; full evasion vs. full compliance) as outcome variable was conducted with income, tax rate, audit probability, and fine level entered as fixed effects (all dummy coded). The model included a random intercept for participants to account for the 24 repeated decisions. The analysis revealed a significant influence of audit probability ($OR = 6.93$, $p < .001$, and $OR = 38.96$, $p < .001$, respectively) and fine level ($OR = 5.49$, $p < .001$), as well as of tax rate ($OR = 1.44$, $p = .017$), but no income effect ($OR = 0.84$, $p = .255$) (see Table 1). Importantly, a higher audit probability and a higher fine level both resulted in increased tax compliance, which is a key assumption of the deterrence approach.

Figure 2 presents the proportion of compliance choices over the 24 rounds of the experiment. For clarity, the rounds were reordered (only for the figure) by increasing expected rate of return from evasion relative to compliance from left to right. Focusing exclusively on the No Expected Value Condition, the proportion of compliant choices was .90, 95% CI [.85, .94], in rounds where the expected value of evasion was lower than the sure gain of compliance; .71, 95% CI [.65, .77], in rounds where the expected value of evasion was equal to the sure gain, indicating that participants were rather risk averse; and .39, 95% CI [.36, .42], in rounds where the expected value of evasion was higher than the sure outcome of compliance, indicating that the proportion of compliance choices was quite high even when evasion was the dominant choice.

One key assumption of the deterrence approach is that there should be a monotonic decrease in relative tax compliance with increasing monetary attractiveness of the evasion option. This means that compliance should decrease steadily from left (round with lowest expected rate of return from evasion) to right (round with highest expected rate of return from evasion) in the displayed order in Figure 2. However, there are deviations from this assumption where compliance increases from left to right, most prominently after the expected return rates increase from .34 to .50 (indicated by non-overlapping 95% CIs).[6]

More precisely, the expected return rate of .34—making evasion more attractive than compliance—applies to two rounds which differ in low or high income (1000 or 3000 ECU), but share a low tax rate (30%), a low audit probability (10%), and a low fine rate (paying back + 100%). In the two rounds with an expected return rate of .50, evasion is even more attractive. They differ from the two previously mentioned rounds as the audit probability is higher (25%) but also the tax rate is higher (50%), the latter making evasion more attractive according to the deterrence model. However, mean compliance is higher in the rounds with an expected return rate of .50 than those with a rate of .34. The striking difference between the rounds with a very similar expected return of .20 and .21 can be attributed to the same pattern of underlying parameters.

These findings suggest that participants seem to overweigh single deterrence parameters (i.e., audit probability) and fail to properly integrate different pieces of information. As the fine is proportional to the evaded tax, the expected return of evasion increases with larger tax rates. This observation represents a clear deviation from the predictions of the deterrence approach.

TABLE 1 Determinants of tax compliance in the no expected value condition

	Tax compliance		
Variables	*Odds ratios*	*CI*	*p*
Intercept	0.07	0.04–0.13	<.001
Income (3000 ECU)	0.84	0.62–1.13	.255
Tax rate (50%)	1.44	1.07–1.95	.017
Audit probability (25%)	6.93	4.74–10.13	<.001
Audit probability (40%)	38.96	24.54–61.87	<.001
Fine level (300%)	5.49	3.96–7.62	<.001

Note: $N = 1272$ observations. Random intercept for $N = 53$ individuals. Independent variables were dummy coded with the lowest level as reference category. The dependent variable, relative tax compliance, was coded with 0 = full evasion and 1 = full compliance. Link function: binomial logit.

3.2 | Acquisition of presented information

To test whether participants acquired all the presented information, we first inspected the acquisition frequencies of each tax parameter for all decisions. We limited this analysis to the No Expected Value Condition, as participants in the Expected Value Condition did not necessarily have to attend to all the presented information to form an

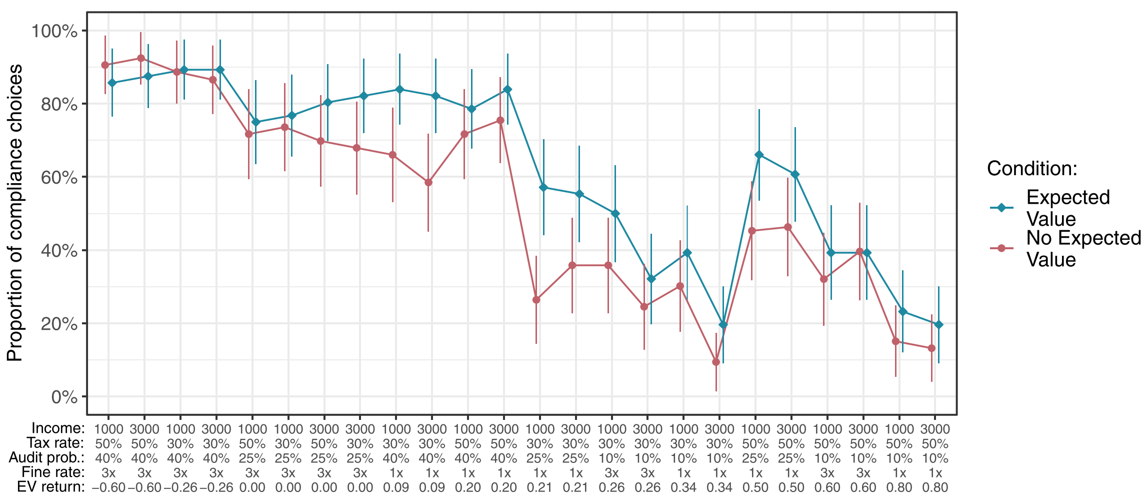

FIGURE 2 Relative compliance over the 24 rounds of the experiment. Note: Rounds are ordered from left to right by increasing expected rate of return from evasion relative to compliance (EV return). In the first four rounds displayed, the expected value of evasion was lower than the sure gain of compliance (as indicated by a negative EV return), in the next four rounds the expected value of evasion was equal (as indicated by zero EV return), and in the remaining 16 rounds the expected value of evasion was higher (as indicated by a positive EV return). Note that this only serves illustrative purposes and was not the round order participants were presented in the experiment, as they faced a randomly predetermined sequence (or alternatively its reversed version) [Colour figure can be viewed at wileyonlinelibrary.com]

expected outcome. As Table 2 reveals, in approximately 95% of decisions, participants opened the four relevant information boxes at least once before their choice. Almost all boxes were revisited at least one more time in approximately 60% of instances preceding the compliance choice. The mean frequency of information acquisitions over the 1272 decisions was $M = 9.01$, $Mdn = 7$, $SD = 6.31$. This means that in line with the minimum requirement of the deterrence model, in almost all decisions, information on each tax-related parameter was inspected at least once.

3.3 | Necessary information acquisition sequences to calculate expected values

The expected value of evasion is calculated by multiplying each possible outcome with its probability of occurrence and subsequently adding up the respective values. More specifically, the probability of no audit has to be multiplied with the financial outcome in case of evasion, and then it has to be added to the probability of an audit multiplied with the outcome in case of detected evasion (i.e., income minus tax due minus fine). Assuming an income of 1000 ECU, a tax rate of 30%, an audit probability of 10%, and a fine level of 100% plus missing taxes, this results in $\text{EV} = .9 \times 1000 + .1 \times (1000 - 300 - 300) = 940$.

In order to compute expected values—at the very least—individuals would be expected to integrate information on audit probability and income as well as information on audit probability and fine level. Assuming that individuals cannot integrate the information only from working memory, we would expect to see transitions between these relevant boxes. Similarly, it can be argued that information likely needs to be revisited to calculate an expected value. It is plausible that the probability of arriving at the correct expected value increases with the total frequency of acquisitions. We tested whether individuals' decisions were more in line with the deterrence approach when more transitions between (1) audit probability and income and (2) between audit probability and fine were observed and (3) when they opened more boxes overall.

To test this, we ran mixed-effects models with compliance as dependent variable (binary, i.e., full evasion vs. full compliance) and the number of audit probability and income transitions, the number of audit probability and fine transitions, and the total number of information acquisitions as fixed effects in separate models considering only the No Expected Value Condition, where expected values were not explicitly presented.[7] The models included a random intercept for participants to account for the 24 repeated decisions. We expected negative associations between indicators of decision processes being in line with expected value-like calculations and compliance in rounds where the expected value of evasion was higher than the sure outcome of compliance (i.e., calculation of the expected value should correspond with lower compliance in these rounds). Assuming risk-averse participants, this association should be reversed in rounds where compliance and evasion were equally attractive and in rounds where the expected value of evasion was lower than the sure outcome of compliance (i.e., calculation of the expected value should correspond with higher compliance).

TABLE 2 Acquisition of relevant information before choosing to evade taxes or to comply

	Frequency of box openings	
Box label	**At least once**	**At least twice**
Income	95.0%	63.8%
Tax rate	94.3%	52.1%
Audit probability	98.1%	58.2%
Fine level	95.2%	57.7%

Note: $N_{\text{choices}} = 1272$.

None of the three fixed effects showed a negative effect in rounds where the expected value of evasion was higher than the sure outcome of compliance; audit probability and income transitions, $OR = 1.09$, $p = .076$; audit probability and fine transitions, $OR = 1.14$, $p = .041$; and total number of information acquisitions, $OR = 1.03$, $p = .043$. Interestingly, in two of these three cases, even the opposite effects were observed, suggesting that individuals who exhibited information processing more in line with expected value-like calculations were more—and not less—compliant.

Likewise, none of the three fixed effects was positive and significant in rounds where compliance and evasion were equally attractive ($OR = 0.92$, $p = .640$; $OR = 0.90$, $p = .463$; $OR = 0.99$, $p = .745$, respectively, in the previous order) nor in rounds where the expected value of evasion was lower than the sure outcome of compliance ($OR = 0.88$, $p = .628$; $OR = 1.09$, $p = .786$; $OR = 0.88$, $p = .462$, respectively, again in previous order).

In sum, decision processes that can be regarded as a prerequisite for calculating an expected value did not correspond with more model-conform decisions as the deterrence approach would assume.[8]

3.4 | Influence of explicitly presenting expected values

In order to evaluate the influence of presenting participants with expected values, we compared compliance over all 24 rounds in the No Expected Value Condition and the Expected Value Condition. For this purpose, we again ran a mixed-effects model with compliance (binary, i.e., full evasion vs. full compliance) as dependent variable and a random intercept for individuals. The condition factor was entered as fixed effect. Against expectation, compliance was higher in the Expected Value Condition compared to the No Expected Value Condition ($OR = 1.70$, $p = .031$). To reveal the source of this difference, we ran separate models for rounds where the expected value of evasion was lower than the sure gain of compliance, for rounds where the expected value of evasion and the sure outcome of compliance were equal, and for rounds where the expected value of evasion was higher than the sure gain of compliance.

Explicitly indicating expected values of evasion did not have a significant effect in rounds where the expected value of evasion was lower than the sure outcome of compliance (No Expected Value Condition: .90, 95% CI [.85, .94], vs. Expected Value Condition: .88, 95% CI [.84, .92]; $OR = 1.24$, $p = .846$). Again, no difference was observed for rounds where the expected value of evasion and the sure outcome of compliance were equal (No Expected Value Condition: .71, 95% CI [.65, .77], vs. Expected Value Condition: .79, 95% CI [.73, .84]; $OR = 2.33$, $p = .158$). However, in rounds where the expected value of evasion was higher than the sure outcome of compliance, presenting expected values resulted in a higher proportion of compliance decisions (No Expected Value Condition: .39, 95% CI [.36, .42], vs. Expected Value Condition: .52, 95% CI [.49, .55]; $OR = 2.06$, $p = .010$). This indicates that presenting expected values did actually not increase the rate of decisions in line with the predictions of the deterrence approach, but—in certain rounds—even yielded a contrary effect. Additionally, we observed the same systematic deviations from stable preference assumptions in the Expected Value Condition, as in the No Expected Value Condition (see Figure 2).

Table 3 informs about interaction effects of income, tax rate, audit probability, and fine level, with the between-subject experimental condition. As established, there were significant effects of audit probability ($OR = 7.25$, $p < .001$, and $B = 42.62$, $p < .001$, respectively), fine level ($OR = 5.73$, $p < .001$), and Expected Value Condition ($OR = 3.22$, $p = .012$) on tax compliance. In addition, there were significant interaction effects for tax rate × Expected Value Condition ($B = 0.60$, $p = .023$) and fine level × Expected Value Condition ($B = 0.53$, $p = .007$), suggesting that a higher tax rate and higher fine had less pronounced effects on compliance in the Expected Value Condition compared to the No Expected Value Condition (see Figure 3).

TABLE 3 Determinants of tax compliance and the effect of presenting explicit expected values

	Tax compliance		
Variable	***OR***	***CI***	***p***
Intercept	0.07	0.03–0.13	<.001
Income	0.84	0.62–1.13	.253
Tax rate	1.46	1.07–1.98	.015
Audit probability 25%	7.25	4.95–10.63	<.001
Audit probability 40%	42.62	26.88–67.57	<.001
Fine level	5.73	4.12–7.97	<.001
Expected value condition (EV)	3.22	1.29–8.04	.012
Income × EV	0.95	0.61–1.46	.809
Tax rate × EV	0.60	0.39–0.93	.023
Audit probability 25% × EV	1.63	0.95–2.81	.078
Audit probability 40% × EV	1.21	0.63–2.34	.564
Fine × EV	0.53	0.34–0.84	.007

Note: $N = 2{,}616$ observations. Random intercept for $N = 109$ individuals. Income was coded with 0 = 1000 ECU and 1 = 3000 ECU; tax rate was coded with 0 = 30% and 1 = 50%; audit probability 25% was coded with 0 = audit probability 10% and 1 = audit probability 25%; audit probability 40% was coded with 0 = audit probability 10% and 1 = audit probability 40%; fine was coded with 0 = paying back plus 100% and 1 = paying back plus 300%; Expected Value Condition was coded with 0 = No Expected Value Condition and 1 = Expected Value Condition; tax compliance was coded with 0 = evasion and 1 = full compliance. Link function: binomial logit.

3.5 | Exploratory analyses: Acquisition of information in relation to tax compliance

In this section, we present further explorations of the information acquisition processes. Figure 4 indicates how often and for how long presented information was acquired and whether there were recurring transitions between certain information boxes, typically reflecting comparisons or information integration. In order to provide a more detailed and meaningful overview, we grouped the acquired information by experimental condition, decision phase, and subsequent compliance decision. Dividing information acquisition into first half (i.e., exploration phase) and second half (i.e., choice phase) is a common approach in process tracing research to offer more fine-grained insights regarding the relevance of acquired information for the final decision (e.g., Johnson et al., 2008; Willemsen & Johnson, 2019).

In the No Expected Value Condition, the income box was opened most frequently and longest compared to the tax rate, audit probability, and fine-level boxes. This difference was primarily observed in the first half of the information acquisition process, but to a similar extent in case of evasion as well as compliance choices. Transitions were observed between all four presented boxes. Similarly, in the Expected Value Condition, income was acquired most often and longest in the first phase in case of both evasion and compliance choices. The boxes sure outcome and EV: evasion (the expected value of the evasion option) were acquired least in this first phase. However, in the second half of the information acquisition process, different patterns were observed in relation to subsequent choices. In case of evasion, the box EV: evasion was opened most frequently and longest, but when compliance was chosen, the box sure outcome in case of compliance was acquired the most. In the latter half of information acquisition, transitions were predominantly registered between the boxes sure outcome and EV: evasion, independent of the subsequent choice (see Figure 4). Table 4 presents the results of four mixed-effects models with frequency and duration (log-transformed) of box openings as fixed effects, respectively, and compliance (binary, i.e., full evasion vs. full compliance) as dependent variable, separately for the two experimental conditions, since the number of presented boxes differed between the No Expected Value Condition (i.e., four) and the Expected Value Condition (i.e., six). The results reveal that in the No Expected Value Condition only frequency of income was a significant predictor of compliance ($OR = 1.19$, $p = .005$). The more often participants in this condition opened the income box, the more

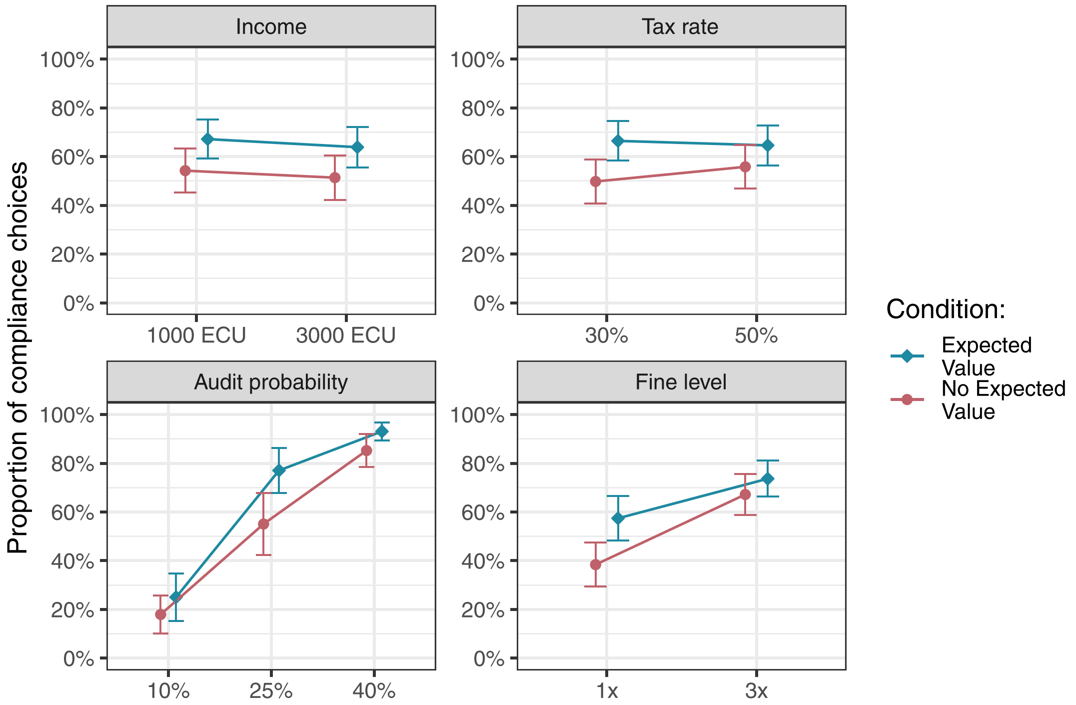

FIGURE 3 Interaction effects of income, tax rate, audit probability, fine level and experimental condition (no expected value condition vs. expected value condition) [Colour figure can be viewed at wileyonlinelibrary.com]

likely they were to be tax compliant. In the Expected Value Condition, both frequency and duration of sure outcome ($OR = 1.62$, $p < .001$, and $OR = 1.22$, $p < .001$, respectively) and EV: evasion ($OR = 0.70$, $p < .001$, and $OR = 0.85$, $p < .001$, respectively) significantly predicted the decision. Opening the box informing about the expected value of evasion was associated with evasion, while opening the box informing about the sure outcome in case of compliance was related to compliance. Additionally, the frequency of opening audit probability was negatively related to compliance ($B = 0.76$, $p = .001$).

Finally, we investigated which box participants opened first and last before deciding whether to comply or evade. In both conditions, the box opened first most frequently was income (35.8% No Expected Value Condition; 26.3% Expected Value Condition), followed by audit probability (29.2% No Expected Value Condition; 23.2% Expected Value Condition). Concerning the last box opened before the final decision, in the No Expected Value Condition, information on audit probability was most frequently opened at last (32.9%). In the Expected Value Condition, sure outcome in case of compliance (41.8%) or EV: evasion (32.1%) was opened most frequently before making the compliance decision. In this condition, last acquisition also predicted compliance decisions significantly. If participants attended the information on the sure outcome in case of compliance at last, they were more likely to pay their tax due ($OR = 2.85$, $p = .042$), and when they attended information on the expected value of evasion just before making their decision, they were more likely to evade ($OR = 0.31$, $p = .021$). There were no other effects of last acquisition on compliance observed.

3.6 | Post-experimental questionnaire

The self-assessment item concerning risk preference indicated that participants were moderately risk-seeking in general ($M = 5.15$, $SD = 2.07$). The willingness to make a risky investment item revealed that 50% were not willing to invest at all, and the majority of those who were willing to invest opted for the two lowest investment levels (18%, and 15%, respectively). Participants who rated themselves as more risk averse were more compliant ($OR = 0.58$, $p < .001$), while choosing a higher risky investment after a previous gain was positively related to compliance ($OR = 1.47$, $p = .002$). Controlling for risk preference when comparing the experimental conditions, the general pattern of results remained unaffected.

Participants in the Expected Value Condition indicated a fair understanding of the concept of expected value ($M = 4.76$, $SD = 1.78$) and stated that they considered expected values in their decisions ($M = 4.33$, $SD = 1.53$). The analysis of the knowledge questions on expected values supports this interpretation to some extent. Twenty-six percent of participants were able to answer all four knowledge questions correctly, 43% were correct on three questions, 16% on two, and 11% on one question, while only 4% were incorrect on all questions.

4 | DISCUSSION

We tested the assumptions of the deterrence approach of income tax evasion within an experimental setting. By recording the process of

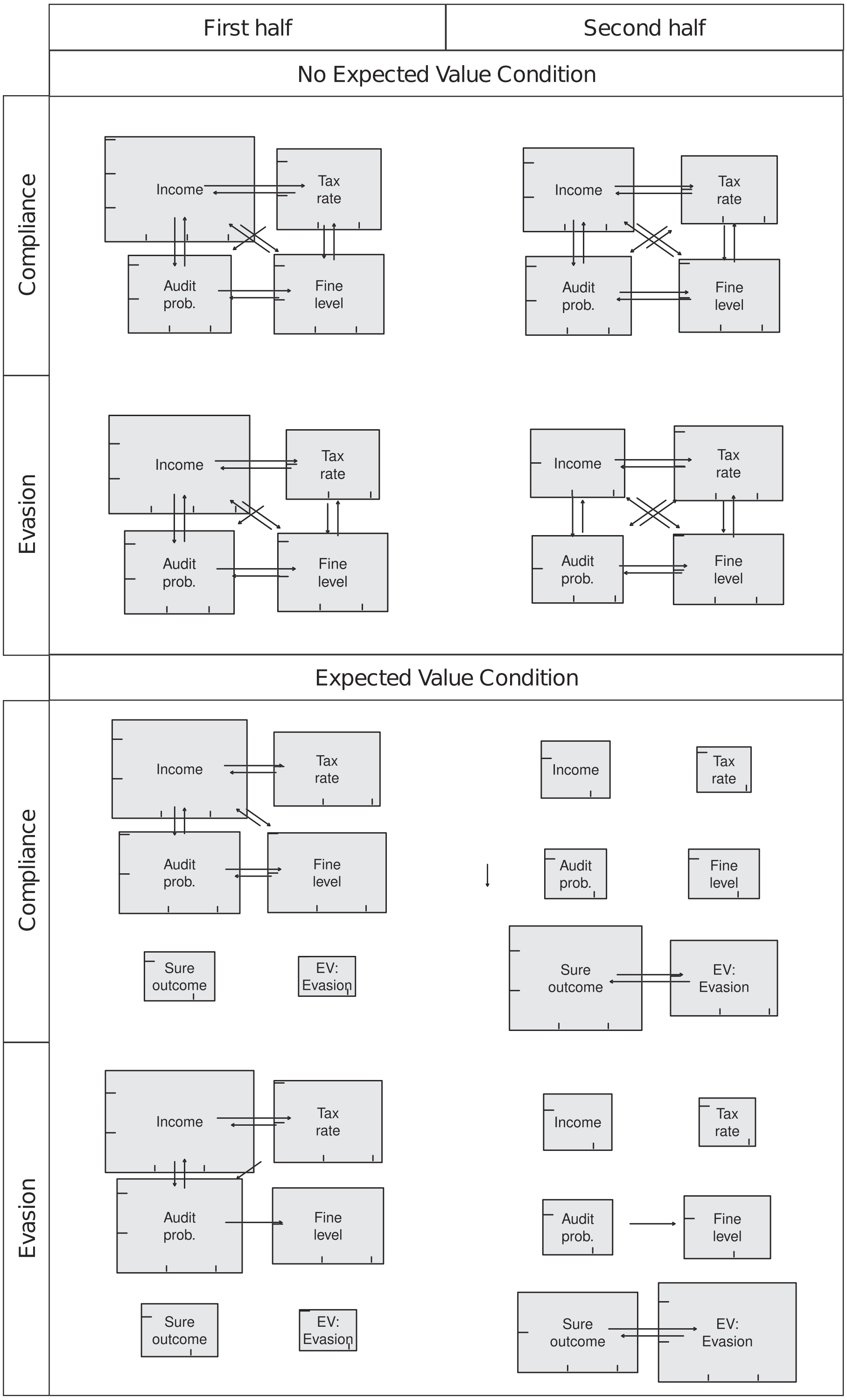

FIGURE 4 Icon graph of the observed process data by condition, decision phase, and compliance decision. Note: The rectangle height corresponds to the average frequency of acquisition, whereas the width to the average duration. Ticks represent 0.5 acquisitions (vertical) and 400 ms (horizontal). The length of arrows represents the frequency of transitions. Transitions occurring fewer than an average of .33 per trial are not displayed for clarity

information acquisition, we can conclude that participants generally attend to the relevant factors introduced in the experiment. As predicted by the deterrence approach, choices were clearly influenced by the direct deterrence parameters. However, against the assumptions of these models, the parameters were not integrated adequately. This is manifested in the violation of the transitivity axiom. Specifically, the Allingham and Sandmo (1972) model expects stable preferences—thus a monotonic decrease in relative tax compliance with increasing deterrence. However, we observe deviations from this assumption which can be explained by focusing on a low (or high) value of one of these parameters and neglecting how this value interacts with other relevant parameters. These findings are in line with observations of inconsistencies in preference and preference reversals in other decision contexts (see, for instance, Payne et al., 1988).

TABLE 4 Frequency and duration of attention to information as predictors of tax compliance for the no expected value condition and the expected value condition

	Compliance in no expected value condition		Compliance in expected value condition	
	Frequency	Duration (log)	Frequency	Duration (log)
Intercept	1.11 (0.77–1.60)	0.38 (0.16–1.10)	2.18** (1.40–3.40)	3.13** (1.39–7.01)
Income	1.19** (1.05–0.34)	1.08 (0.96–1.22)	0.97 (0.84–1.11)	0.91 (0.83–1.00)
Tax rate	0.90 (0.79–1.02)	1.04 (0.94–1.16)	1.06 (0.90–1.24)	1.02 (0.94–1.11)
Audit probability	0.96 (0.85–1.09)	1.06 (0.91–1.24)	0.76** (0.64–0.90)	0.90 (0.80–1.02)
Fine	0.95 (0.84–1.08)	0.97 (0.86–1.09)	1.03 (0.88–1.21)	1.06 (0.97–1.16)
Sure outcome			1.62*** (1.40–1.88)	1.22*** (1.12–1.34)
EV: Evasion			0.70*** (0.60–0.80)	0.85*** (0.78–0.91)

Note: $N = 56$ (1344 observations) for the No EV condition and $N = 53$ (1272 observations) for the EV Condition. Random intercept for $N = 109$ individuals. Odds ratios (OR) and confidence intervals (CI) in brackets are indicated for each variable and condition. Frequency was measured by how often a certain box was opened per round; Duration is the log transformed duration in milliseconds a certain box was opened per round; tax compliance was dummy coded with 0 = evasion and 1 = full compliance. Link function: binomial logit.

** $p < .01$.

*** $p < .001$.

These instances cannot be explained by general ignorance of relevant information or lacking skills to calculate expected values. Moreover, we also observe transitions between the relevant parameters, indicating that they could have been considered simultaneously, but—as previously explained—this does not occur in line with expectation formation in terms of the deterrence model. Additionally, participants in a condition where expected values were presented explicitly (along with an explanation of the concept of expected value) showed the same inconsistent choice patterns.

In general, our findings are in line with previous research in the field of tax behavior suggesting that tax compliance decisions cannot be explained comprehensively only by considering economic determinants (e.g., Alm et al., 1995; Cowell, 1992; Kirchler, 2007; Wenzel, 2004). However, the main contribution of the present study also differs from this existing body of literature. Our findings suggest that even in a rather artificial situation, where other (noneconomic) factors are of negligible concern, important assumptions of the deterrence approach are challenged. Importantly, it is not the case that people do not react to audit probabilities or severity of fines; however, they do not consider them as predicted by the deterrence model. For instance, we find a clear difference in the proportion of compliance choices between rounds that are equally attractive in terms of monetary prospects. Additionally, compliance proportions even increase where the model would predict decreasing compliance. The finding that individuals react only to changes in a single parameter, while neglecting the integration of multiple deterrence relevant information pieces, is in line with the mixed evidence in the crime deterrence literature concerning an interaction effect of detection probability and severity of sanctions (Carroll, 1978; Howe & Loftus, 1996; Stafford et al., 1986). On a theoretical level, these findings challenge the universal assumption that people have stable preferences based on expected values and that these preferences are revealed through their decisions (see McFadden, 2001; Orquin & Mueller Loose, 2013). We also observe that participants seem to be influenced stronger by information on audit probability rather than on fines, which is in line with evidence in the literature (see Alm & Malézieux, 2021). However, given that it is unclear whether the differences between the presented levels of the respective variables are equivalent, this specific finding of our study should be interpreted with caution. Regarding income and tax rate effects, we found no effect of income but a positive effect of tax rate on compliance which corresponds to the theoretical prediction by Yitzhaki (1974) but runs counter to most empirical findings (Alm & Malézieux, 2021; Malézieux, 2018).

Another important result that conflicts with the deterrence approach is that expected value-like information processing patterns did not result in choices being more in line with the predictions of these models. Accordingly, more transitions between audit probability and income as well as between audit probability and fine level did not increase model-conform compliance decisions. This can be interpreted as additional evidence that these parameters are not considered simultaneously as calculating an expected value would require such transitions. Our findings suggest that presented expected values are not considered correctly, which corresponds to evidence from previous studies in the domain of gambles (for instance, Li, 2003; Lichtenstein et al., 1969). More importantly, we also obtained one rather surprising finding, namely, that explicitly indicating expected values resulted in more compliance in rounds where expected value of evasion was higher than the sure outcome of compliance. The simplest explanation for this might be that participants did not understand the provided explanation of the concept of expected values and thus did not (adequately) consider them in their decisions. Although possible, this is rather unlikely, as participants indicated that they understood the provided explanation and that they considered expected values in their choices. In a number of exploratory analyses excluding outliers based on decision times (see Figure S5 and Table S1), we find that our results are quite consistent applying different exclusion criteria. Only in case we apply a very stringent criterion where approximately 25% of our sample would be excluded, this effect is not statistically significant anymore (but still in the same unexpected direction). Accordingly, we are quite confident that this finding is systematic and not attributable to a few outliers in our data.

Apart from problems in understanding expected values, another explanation for the observed difference between the two conditions might be a different representation of the decision outcomes similar to some sort of anchoring effect (see, for instance, Chapman & Johnson, 1999; Mussweiler & Strack, 2001; Tversky & Kahneman, 1974). Consider the following situation, with an income of 1000 ECU, a tax rate of 30%, an audit probability of 10%, and a fine level of 300%: in the No Expected Value Condition, the two compared options might be represented as sure outcome of 700 ECU in case of compliance (by considering the income and the tax rate) and a risky outcome of 1000 ECU in case of undetected evasion, if an individual is in principle willing to accept the risk of evasion. In the Expected Value Condition, this representation might be a comparison of the sure outcome of 700 ECU and the expected value of evasion, that is, 880. In such a situation, the expected value could falsely be represented as a potential (risky) outcome similar to the potential maximum outcome of evasion in the other condition, rather than a long-term prospect of multiple outcomes. As a consequence, the smaller difference between 880 and 700 compared to 1000 and 700 would make the evasion option appear less attractive in the former case. It has been shown that anchoring effects are often immune to corrective attempts (Wilson et al., 1996), which might have attenuated the explanation of the concept of expected values provided to participants in our study.

An alternative explanation for the observed difference between the two conditions could be related to the labels of the additional information boxes in the expected value condition (i.e., Sure outcome; EV: evasion). The word "sure" might have enhanced the attractiveness of this choice option, that is, full compliance, while the word "evasion" might have activated stronger norm obedience (see, for instance, Baldry, 1986; Mittone, 2006), in combination promoting higher compliance. However, given that in both conditions a strong tax frame was used, we believe it is rather unlikely that the two additional box labels would overshadow or even reverse an effect of explicitly presented expected values.

Concerning the relation of information acquisition and compliance decisions, we identified three interesting patterns. First, when expected values were not explicitly indicated, more frequent attention to income was correlated with higher compliance. Although we cannot make any causal inference here, this observation might be well explained by Prospect Theory (Kahneman & Tversky, 1979). Focusing stronger on income makes the endowment, and thus, the potential payoff more salient, resulting in less risk-seeking. Second, participants who were explicitly provided with expected values can be split into two subgroups. Those who focused more on the sure outcome of compliance were likely to be more compliant, while more frequent and longer attention to the expected value of the evasion option was associated with a higher probability to evade. We believe that this pattern likely reflects a so-called gaze cascade effect, which describes the phenomenon that gaze is gradually shifting toward the chosen option, assuming that gaze is actively involved in preference formation (e.g., Shimojo et al., 2003). Third, when expected values were indicated, paying more attention to audit probability corresponded with lower compliance. Notably, in this situation, the audit probability does not necessarily have to be checked, since the expected value is explicitly provided. Hence, participants who have the intention to evade might pay extra attention to the specific information on audit probability. Such interindividual differences in information acquisition offer a promising avenue for tax behavior research.

With regard to the processing of information, one important concern is whether MouselabWEB actually allows to inform about the cognitive processes underlying decision making. MouselabWEB can be considered as analogous to eye-tracking, and eye movements and mouse movements have been shown to correlate (see, e.g., Chen et al., 2001). While visual traces are of course only indicators of external attention, they are rich in providing such information and have been proven to help in explaining cognitive processes in different fields of psychology (for an overview, see, for instance, Rahal & Fiedler, 2019). Particularly, process tracing methods can be used to test the predictions of decision-making theories, whenever it is possible to derive such predictions of attention to visual stimuli. With the current study, we aimed to provide such an analysis for the deterrence model of tax evasion, where such an effort is to date missing. As shown by previous attempts to test expected value based models (e.g., Orquin & Mueller Loose, 2013), it is possible to derive testable process predictions from the deterrence model that can expose theoretical limitations of current decision models. As our results show clear deviations from these assumptions, we are confident that this approach does reveal important insights about the decision process that would not be obtainable with choice data or structural modeling alone.

Another related issue is whether applying MouselabWEB to investigate underlying cognitive processes might have altered the cognitive process and thus prevented decision making in line with the assumptions of the deterrence model. The literature has presented evidence that Mouselab does monitor cognitive process in decisions without producing significant changes in cognition (Willemsen & Johnson, 2019). Actually, the specific features of MouselabWEB being more time consuming since the boxes hiding relevant information have to be opened deliberately make it especially convenient for investigating controlled information acquisition as compared to, for instance, eye-tracking, which is better applicable to more automatic decision making (e.g., Glöckner & Herbold, 2011; Lohse & Johnson, 1996; Norman & Schulte-Mecklenbeck, 2009). Hence, MouselabWEB should have rather enhanced controlled and deliberate decision making than suppressed it.

One potential limitation of the present study relates to the sample selection. The participants were students from different social and natural sciences disciplines, and thus, it is questionable how generalizable the observed results are. There is conflicting evidence on whether student samples in tax experiments differ in their behavior from (more) experienced taxpayers (e.g., Choo et al., 2016) or not (e.g., Alm et al., 2015; Wahl et al., 2010). However, this might be less of a problem in the current study, since the setting is by intention rather artificial. Accordingly, a more tax-experienced sample or a more realistic setting than in the current study might even decrease consideration of expected values. Another potential limitation are specific features of the design as presenting the tax compliance decision as a dichotomous choice between full evasion and full compliance only or providing feedback on whether an audit took place delayed to the end of the repeated decisions. We believe that both of these features also applied in other tax experiments offer more advantages than disadvantages in the current setting by allowing to present single explicit expected values and avoiding often observed reactions to audits, so-called bomb crater effects (e.g., Mittone, 2006) describing strong decline in compliance in subsequent rounds, respectively.

In a nutshell, we conclude that deviations from the deterrence approach in tax compliance experiments cannot be explained by attentional neglect of diagnostic information. Observed deviations from the predictions most likely are due to incorrect integration of relevant information. When decisions in line with the assumptions of the deterrence model are facilitated by indicating explicit expected values, actual choices do not conform more to the predictions. Although we discuss potential explanations for this finding, we believe that the specific representation of outcomes and the influence of variations in the specific materials used should be addressed in future research.

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CONFLICT OF INTEREST

None.

ENDNOTES

[1] Tax compliance decisions in real life are usually decisions under uncertainty, where possible outcomes and their respective probabilities are not (explicitly) known. In experiments on tax compliance, these outcomes and their probabilities are often explicitly communicated, and accordingly, they investigate decisions under risk.

[2] Independently, Srinivasan (1973) developed a similar model to explain income tax evasion. Since the Allingham and Sandmo version has received more attention in the literature over the years, we mainly refer to this model here in the introduction. However, both models as well as later extensions do not differ in the relevant predictions that are the main focus of this study. Thus, we will refer to all theoretical models in the spirit of the Allingham and Sandmo model as the deterrence approach or as deterrence models.

[3] No prior study in the domain of tax compliance decisions was informative of an expectable effect size for the difference in compliance between the No Expected Value Condition and the Expected Value Condition (see section 2.2).

[4] Offering only two choices also corresponds to many real-life situations where the options of full compliance or full evasion emerge, for instance, when deciding whether or not to declare extra income.

[5] Participants were informed that the show-up fee would be paid independent of the decisions in the experiment. Thus, the minimum final payment was 2 euro.

[6] Note that such deviations also become apparent if rounds are ordered by the absolute difference between the expected value of evasion and the sure outcome of compliance.

[7] Note that the same pattern of results is observed when using binary transition indicators (transition present or not present in a decision) as fixed effects and also when entering all fixed effects simultaneously (see Tables S2–S7).

[8] In the Expected Value Condition—where such transitions would not be necessary to determine Expected Values—the number of transitions does also not predict decisions that are more in line with the assumptions of the deterrence model.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the Open Science Framework (OSF) at https://osf.io/h3ja6 or https://doi.org/10.17605/osf.io/h3ja6.

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