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How explicit expected value information affects tax compliance decisions and information acquisition

Martin Müller[a], Jerome Olsen[b], Erich Kirchler[a,c], Christoph Kogler[d,*]

[a] University of Vienna, Faculty of Psychology, Department of Occupational, Economic and Social Psychology, Universitaetsstrasse 7, 1010 Vienna, Austria
[b] Max Planck Institute for Research on Collective Goods, Kurt-Schumacher-Straße 10, 53113 Bonn, Germany
[c] IHS - Institute for Advanced Studies, Josefstaedterstrasse 39, 1080 Vienna, Austria
[d] Tilburg University, School of Social and Behavioral Sciences, Department of Social Psychology, Warandelaan 2, 5037AB Tilburg, The Netherlands

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ABSTRACT

In a MouselabWEB experiment with 345 participants, we investigated whether different presentations of expected value information in tax compliance decisions increase conformity with classical deterrence models' assumptions. Recording both choice and process data, we compare conditions of verbal explanation only, verbal explanation plus numerical cue, verbal explanation plus visual cue, and a control condition without expected value information. Only when the expected value was presented as a visual cue the option with the higher expected value (i.e., evasion) was chosen more often than the control condition (58.3% vs. 38.4%). Nevertheless, individuals were more compliant than predicted by the deterrence model. While we identified differences between the experimental conditions in information acquisition patterns and decision times, they do not suggest that one way of presenting expected value information was easier to process than the others or that the main behavioral effect can be explained by higher saliency of the visual cue. These results indicate that individuals' decisions are not predominantly driven by outcome maximization, even when explicit expected value information is provided.

1. Introduction

The most influential classical theory in tax literature is founded in the seminal work by Allingham and Sandmo (1972) and Srinivasan (1973), who applied the economics-of-crime approach by Becker (1968) to tax reporting behavior. Considerable extensions to the standard model have been added over the years (for an overview, see Alm, 2019; Andreoni et al., 1998); however, the basic premise of the deterrence approach[1] stayed the same. Taxpayers choose between compliance and evasion based on a simple cost-benefit analysis. If deterrence is low (i.e., low audit and fine rates), evasion is likely; if deterrence is high, taxpayers choose to pay the taxes they owe.

Despite the widespread application of the deterrence approach, there is mounting evidence pointing at its limitations (Alm & Malézieux, 2020; also see Pratt et al., 2006 for a meta-analysis of non-tax related deterrence studies). Most importantly, the deterrence

* Corresponding author.
E-mail address: c.kogler@tilburguniversity.edu (C. Kogler).

[1] We refer to all theoretical approaches to tax evasion based on the economics-of-crime paradigm (Becker, 1968) as the deterrence approach, since the underlying rationale is that tax evasion mainly depends on the severity of deterrence.

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approach strongly overpredicts noncompliance rates. In most countries, the probability of being audited and the subsequent fines for detected tax evasion are relatively low. Consequently, we would expect high rates of tax evasion. Most taxpayers, however, comply with the tax laws (Alm, 2019; Alm et al., 1992; Andreoni et al., 1998; Bernasconi, 1998). Even in the artificial and simplified environment of the research lab, compliance is usually found to be higher than the deterrence approach predicts (Alm et al., 1992, 2010; Alm & Malézieux, 2020; Engel et al., 2020; Slemrod, 1992; Torgler, 2007). In addition, selected studies fail to find positive deterring effects of audits and fines (Iyer et al., 2010; Kirchler et al., 2010; Slemrod et al., 2001; Spicer & Thomas, 1982). Despite acknowledging these limitations and efforts to incorporate psychological considerations, the deterrence approach has remained at the core of most analyses of income tax evasion.

The deterrence approach assumes taxpayers to behave as if maximizing some form of expected utility (EU; Allingham & Sandmo, 1972; von Neumann & Morgenstern, 1947) or expected value (EV) of income (Srinivasan, 1973) by a process that can be described as weighing and adding (Su et al., 2013). Accordingly, taxpayers weigh each outcome by its probability, summarize all the possible outcomes to assign an overall value (expectation) to each option, and then select the option that offers the highest expectation. It is not argued that taxpayers are necessarily doing these calculations but that they behave as if they maximize their expectations. Thus, the model produces testable predictions about aggregates of behavior. If they turn out to be correct, it can be argued that individuals really behave as if they are axiomatically assumed to behave, regardless of whether the model is based on realistic assumptions about the cognitive processes underlying tax compliance decisions.

This as-if approach was challenged by process-tracing methods like thinking aloud (Montgomery & Svenson, 1989), mouse-tracking (e.g., MouselabWEB; Willemsen & Johnson, 2019), eye-tracking (Rayner, 1998), and brain imaging (e.g., fMRI; Bennett et al., 2009). These tools have led to advances towards unpacking the black box by allowing researchers to derive insights about cognitive processes underlying decision making (Camerer et al., 2005; Fifić et al., 2019; Schulte-Mecklenbeck et al., 2011). Consequently, the focus of research in the field of judgment and decision making (JDM) has shifted from merely attempting to understand what people choose to how they actually arrive at their decisions (Ford et al., 1989; Krajbich et al., 2010). Similar arguments were also made for economic research (Johnson & Ratcliff, 2014; Levitt & List, 2009). However, this important and insightful paradigm shift has been basically neglected in tax research so far.[2]

Importantly, JDM research has basically focused on the gambling context investigating the role of EV and EU in decision making. Despite structural similarities, the setting in tax compliance studies is not directly comparable. Even in lab studies participants know that compliance is the normatively expected behavior (Bruttel & Friehe, 2014), as ethical and moral considerations influence tax behavior (Alm & Torgler, 2006; Torgler, 2002). Additionally, factors like fairness perceptions and social norms often influence compliance decisions (e.g., Kirchler, 2007; Wenzel, 2004), which makes tax decisions more complex than risky gambles. Furthermore, tax decisions are basically focused on the domain of losses, which facilitates risky decisions (i.e., evasion) compared to the gambling context studying the gain and loss domain (e.g., Weller et al., 2010). Accordingly, it has been pointed out that compliance in a tax setting is typically higher than risky choice rates in a pure gambling context, and the experimental framing (tax vs. gamble) observed to interact with other variables such as participants' age and audit probabilities (see Muehlbacher & Kirchler, 2016).

Although experiments exclusively analyzing decision outcomes provide considerable evidence for testing decision models, different models may predict the same outcome or preference despite potential differences in the underlying cognitive processes (Johnson et al., 2008). Thus, it is difficult to justify decision models without examining the underlying process, even when the outcome data is correctly predicted. By recording the acquisition of information, it is possible to directly examine the processes underlying tax decisions to explain when and why important axioms of risky decision making are violated (Payne et al., 1993; Schulte-Mecklenbeck et al., 2011). If the deterrence approach's axiomatic assumptions, however, do not correspond to actual decision processes, then the model may predict but not really explain at all.

In a recent experiment (Kogler et al., 2022) we first applied MouselabWEB, a tool to record the acquisition of information via a computer mouse, to a simple tax evasion game in the realm of the deterrence approach, assuming a linear utility function.[3] This study investigated whether individuals actually behave as assumed by the deterrence approach. That is, whether individuals integrate outcomes and probabilities in what can be called a compensatory weighting and adding process (Su et al., 2013). To this end, we tested the implicit assumptions about the underlying decision process that can be theoretically derived from the deterrence approach (see Orquin & Mueller Loose, 2013). Based on both the process and behavioral data, we found evidence against the main assumptions of the deterrence approach.

First, model-conform decisions were not associated with information acquisition patterns that indicate more EV-like calculations: more transitions between audit probability and income, more transitions between audit probability and fine, or more box openings in general. Second, compliance was considerably higher in general than the model would predict, although the overall trend was in accordance with the tax-related deterrence parameters. Finally, explaining and providing explicit information about EV did not

[2] Notable exceptions are Harbaugh et al. (2007) applying fMRI, Enachescu et al. (2021) and Coricelli et al., (2010) measuring skin conductance responses, Dulleck et al. (2016) applying heart rate variability, Gangl et al. (2017) measuring EEG, and Balconi et al. (2019) using a combination of EEG, heart rate variability, and electrodermal activity.

[3] We are closer to Srinivasan (1973), assuming participants are maximizing the expected income after tax and penalties, than to the assumptions of Allingham and Sandmo (1972) that individuals are maximizing their EU. However, predictions stay the same: increasing the deterrence parameters, audit probability and fine rate, leads to an increase in tax compliance.

enhance model-conform decisions. Interestingly, in some rounds, we found a reversed effect[4] in the proportion of tax compliance decisions when comparing one group with explicit numerical EV information against a group where the concept of EV was only explained verbally. In other words, when we presented participants with explicit numerical EV information, this did not lead to more decisions in line with EV, but we even observed the opposite, that explicit EV information led to more compliance in rounds where EV clearly favored evasion. However, it remains an open issue how generalizable this finding is, as we tested one specific presentation variant of expected value information, and the control condition also received a verbal explanation of EV information (but not the explicit EVs).

1.1. *Aim*

This study aims to build on this previous result but moves one step further in the way explicit EV information is presented. Specifically, we are interested in whether the deterrence model's choice predictions and implicit process assumptions hold at the latest when we make the explicit EV information, indicating the optimal choice, more salient and straightforward. This more accessible presentation format will allow us to also generalize beyond a mere numerical presentation of EV and to investigate whether different ways to convey EV information have distinct effects on individuals' choices and information processing. Consequently, the current study builds on our recent experiment (Kogler et al., 2022) in two ways:

First, we introduced three different variants of communicating and presenting EV information. We compare tax decisions where (1) neither verbal explanation of the concept of EV nor explicit EV information is provided (i.e., control condition) with decisions where we only (2) verbally explain the concept of EV before the actual compliance decisions (i.e., verbal condition), (3) verbally explain the EV and present the concrete numerical values for each compliance decision (i.e., numerical condition), and (4) verbally explain the EV and present explicit EV information in the form of a visual cue (i.e., visual cue condition). Accordingly, comparing the verbal condition with the numerical condition represents a conceptual replication of Kogler et al. (2022), while the comparison between the numerical condition and the visual cue condition allows us to generalize our findings beyond a numerical representation of EV. In this way, we can systematically investigate whether individuals consider EV information in tax decisions when such information is made accessible and comprehensible and how the availability of EV information potentially alters the decision-making process.

Second, we implemented an extensive introduction where all parameters, including the EV, were explained in great detail prior to the experiment. We included several checks to ensure that participants understood the study instructions, the explanation of the tax parameters, and the EV concept. In doing so, we could ensure that participants really understood what decision-making processes would be necessary to make model-conform tax decisions to an even more substantial degree than in the original study.

As a result, the present study should pose an even more critical test of the basic assumptions of the deterrence approach on the behavioral level as well as on the level of cognitive processes. According to the deterrence model, individuals should consider EV information in tax decisions when such information is made accessible and comprehensible and adjust their preferences accordingly. If the more comprehensible visual cue, however, does not lead to a significant increase in model-conform decisions and the information acquisition is not indicative of a process of weighting and adding, this study would yield important evidence that tax compliance decisions are not primarily guided by EV considerations. Then we argue it is evident that the deterrence approach does neither sufficiently predict nor explain tax compliance decisions, not even in lab situations where information on tax parameters is both explicit and strongly emphasized. Based on the between-group comparisons, we make several preregistered predictions (https://osf.io/zbr2g) on both the behavioral and process level.

1.1.1. *Behavioral level hypotheses*

The deterrence approach assumes that decision-makers have stable preferences that can be revealed through their decisions (McFadden, 2001; Orquin & Mueller Loose, 2013). Therefore, we expect that explaining the EV concept or the numerical and visual explicit presentation of EV will result in more model conform tax compliance decisions compared to decisions where no explicit EV information is provided. Consequently, we expect more model conform decisions in the visual cue, numerical, and verbal conditions compared to the control condition (H1).

If we assume a more realistic approach where decision-makers apply a decision strategy or heuristic that serves as a shortcut to decision making (bounded rationality; Simon, 1957), individuals should at least adjust their preferences when presented with explicit EV information. We vary the saliency and simplicity with which the EV information reveals the model-conform preference (i.e., numerical vs. visual presentation); thus, we expect that the three EV conditions differ in the extent the decisions conform with the predictions of the deterrence approaches. Further, graphical representation of data might reduce the cognitive load (Chandler & Sweller, 1992) compared to only a numerical representation, leaving more cognitive resources available for decision making. For example, it has been shown that a well-designed visual display can reduce the amount of mental computation by replacing it with automatic visual perception (Wickens & Carswell, 1995). Accordingly, comparing the three EV conditions, we assume the visual cue condition to be most effective, followed by the numerical condition, and finally, the verbal condition being least effective in increasing model conform decisions (H2).

Additionally, we investigate whether individuals react to changes in tax parameters in accordance with the assumptions of the

[4] The difference between the groups was no longer significant, after excluding participants who deviate by more than 1 SD from the overall box opening times.

deterrence approach.[5] Based on theoretical and empirical evidence, we expect both higher audit probability and higher fine rate to have a deterrent effect on tax evasion (Alm & Malézieux, 2020; Andreoni et al., 1998; Fischer et al., 1992). Concerning the effect of tax rate and income, both are ambiguous from a theoretical and empirical perspective (Kirchler et al., 2010). Based on the A&S model, either the return of compliance decreases as the tax due is increasing, because the fine is proportional to the tax rate (i.e., the substitution effect), or compliance increases as income decreases, potentially leading to higher risk aversion (i.e., the income effect). However, as shown by (Yitzhaki, 1974), when the fine rate depends on the evaded tax rather than the non-declared income, as in the present experiment, the substitution effect disappears and only the income effect remains. Consequently, we predict that higher tax rates reduce tax evasion but do not make predictions concerning the relationship between income and tax compliance.

1.1.2. Process level hypotheses

We derive multiple predictions from the axiomatic assumptions of the deterrence approach on the process level. First, when choosing between different options with uncertain consequences, decision-makers must inevitably attend to all relevant information. Two basic assumptions underlying the interpretation of visual information acquisition are that information used in decisions must be acquired and that information acquisition is temporally proximal to information use (Costa-Gomes et al., 2001). Thus, we expect more extensive information search in the verbal condition than in the control condition. This will translate into more inspected information and longer box openings in the verbal condition (H3a).

Second, for each choice option, payoff and probability must be determined and multiplied to obtain the long-term payoff prospect for each option (i.e., EV). These prospects are then compared to each other, and a final decision is made. Hence, certain transitions between the provided information can be expected (Orquin & Mueller Loose, 2013). We predict more such EV-like transitions in the verbal condition than in the control condition. This translates into more transitions between audit probability and income as well as between audit probability and fine (H3b).

Further, we make several predictions concerning the ease of information processing between the conditions. Under the assumption that individuals attend to the explicit EV information and explanation, we expect that a visual EV cue is easier to process than a numerical EV cue which is easier to process than a verbal EV explanation of how to calculate an EV. The ease of information processing should be negatively correlated with decision times as well as with the number of inspected information (box openings in total/displayed number of boxes) (H4).

Given that explicit EV information should be easier to process in the visual cue condition than in the numerical condition, we expect that individuals in the visual cue condition will put more relative attentional weight on the explicit EV information than those in the numerical condition. Compared to the numerical condition, in the visual cue condition we should observe a higher proportion of attention to explicit EV information in comparison to the four classical tax-related information boxes. This must not be a function of individuals inspecting the explicit EV information longer or more often in the visual cue condition, but rather them placing less emphasis on the four tax-related boxes (income, tax rate, audit probability, and fine level) (H5).

2. Method

2.1. Participants

A total of 397 participants were recruited through Prolific. Prescreening criteria on Prolific were set to UK nationality and a minimum study approval rate of 97/100. Fifty-two individuals were excluded based on preregistered criteria (28 failed checks, 10 participated multiple times, 18 had technical problems or used an unsupported device like a tablet; some individuals met multiple exclusion criteria). The final sample size was $N = 345$ (165 women and 180 men) with a mean age of 35.3 years ($SD = 13.0$, $Min = 18$, $Max = 80$).

2.2. Design and procedure

2.2.1. Manipulation and tax decisions

We applied a repeated measures design where the dependent variable tax compliance (dichotomous choice; full evasion vs. full compliance) was measured 24 times. Four within-subject factors varied the tax-related decision parameters resulting in 24 unique rounds: Income (1200 vs. 1400 Experimental Currency Units (ECU)), Tax Rate (25 % vs. 40 %), Audit Probability (10 % vs. 20 % vs. 30 %), and Fine Level[6] (paying back the evaded amount plus a fine of 50 % vs. paying back the evaded amount plus a fine of 100 %). In all rounds, the EV of not paying tax was higher than the sure gain of paying tax; thus, evasion was always preferable from a position of EV optimization (assuming risk-neutral agents). The order of rounds was random for each participant.

In four between-subject groups, we manipulated the presence or absence of explicit EV information and how this additional information was explained: (1) control condition (i.e., no explicit EV explanation), (2) verbal condition, (3) numerical condition, and (4) visual cue condition.

Participants were first presented with a general introduction in all four conditions that explained each of the four tax-related

[5] This standard analysis was not explicitly indicated in the preregistration.

[6] Note that we deviate from the original formulation of the A&S model here. Instead, we use the correction of Yitzhaki (1974) that makes the fine proportional to the unpaid tax.

parameters in detail. This included the financial consequences of each of the two choice options in case an audit occurred or not. The instructions were structurally the same in all four conditions but included additional information depending on the condition. They did not mention any explicit EV explanation in the control condition. In the three remaining conditions, the introduction also provided explanations on what the EV meant, how it can be used to arrive at mathematically optimal decisions, and how it can be calculated given the provided tax-related parameters presented in each round.

In two of the EV conditions, participants additionally received explicit EV information during the decision rounds, explained in detail before the decision phase. In the numerical condition, participants were provided with the precalculated numerical EV as well as sure outcome values. In the visual cue condition, the same information was presented in a stylized format using a circle that illustrates the relative size of the difference between the EV and the sure outcome (see Fig. 1). In this presentation, the more attractive evasion is, the further the pointer deviates from the black horizontal line that presents a neutral position to the endpoint of "don't pay" (=full evasion). In all three EV conditions, individuals were not explicitly instructed to follow the EV information. Instead, they were told that this information could be used (and explained how exactly) if one wanted to make mathematically optimal decisions. The instructions were pretested with $N = 63$.

2.2.2. MouselabWEB design

The information in each round was presented using MouselabWEB (Willemsen & Johnson, 2019), where the information of each of the four tax parameters is hidden behind labeled boxes. Participants had to move the mouse cursor over a box to reveal the respective information. Once the mouse cursor was moved outside the respective box, this information was hidden again. A fixation cross (50 × 50 px) was presented for two seconds between rounds. There were two orders of how the boxes were arranged on the screen to control for possible position effects (see Fig. 1). One of the two orders was randomly determined in the first round for each participant, and this presentation order was the same for all 24 decision rounds. Frequency, duration, and sequence of information acquisition were recorded via MouselabWEB.

2.2.3. Pre- and post-experimental measures

The study contained several additional measures at different stages of the procedure. After a general introduction to the study and the incentivization mechanism, participants had to answer to a general risk question taken from the German Socio-Economic Panel (Dohmen et al., 2011; "How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?", 10-point scale from 0 = Definitely avoiding to take risks to 10 = Fully prepared to take risks) followed by an incentivized lottery-choice task (Holt & Laury, 2002). After detailed instructions on the repeated rounds of tax evasion decisions, the first block of

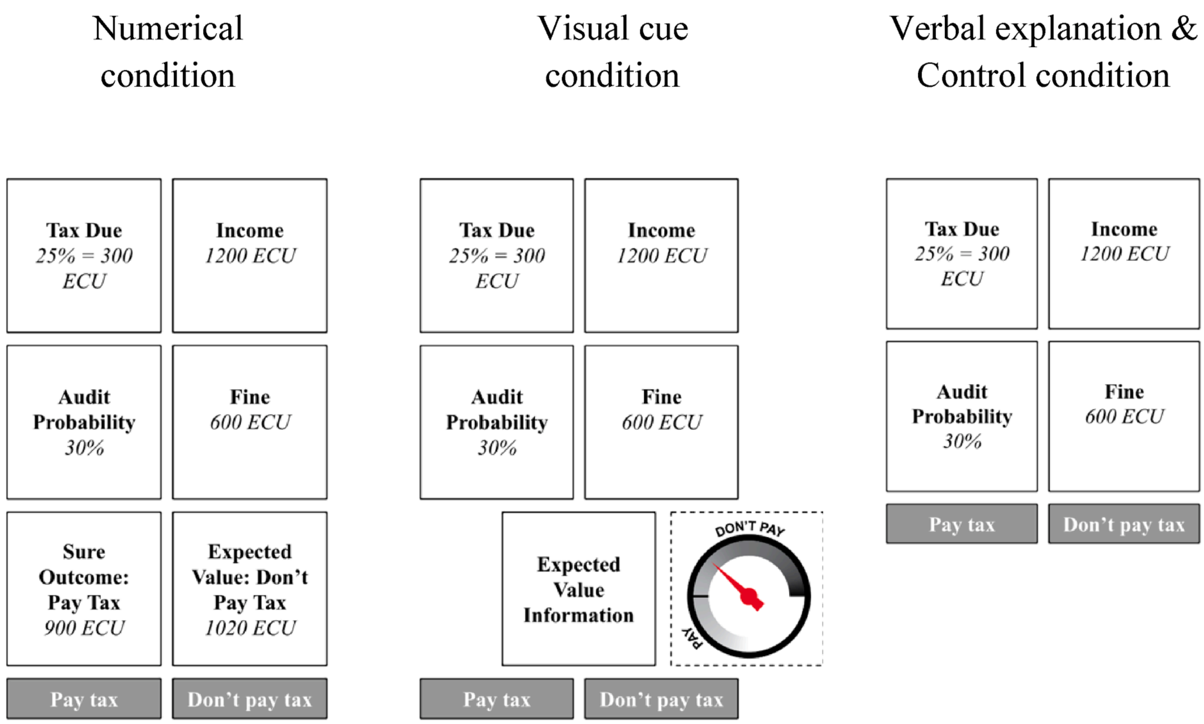

Fig. 1. Schematic illustration on how information was presented in the four experimental conditions Note. The position of the boxes was systematically varied between participants by flipping the boxes diagonally. In the verbal and the control condition the same information was displayed, only the explanations prior to the experimental rounds differed. Note that the values (Italic) and the visual cue are shown for presentational purpose only and, in the actual experiment, were only visible after moving the mouse cursor over the respective box.

four comprehension check items (e.g., "How much would your remaining income be, if you choose "don't pay" and there is no audit?") was presented to test whether participants understood the tax parameters. After completing the tax rounds, participants received audit feedback for all 24 rounds.

The post-experimental questionnaire consisted of a second block of eight comprehension check items (e.g., "The expected value of evasion represents the average outcome of choosing tax evasion."; Answer options: False, True, Do not know). Participants in the *control condition* were only presented with the four items concerning the four tax parameters as the concept of EV was not explained to them. Two additional questions about the parameter values (e.g., "Which tax rates were used over the repeated decisions in the second part?"; answer options: 25 % and 40 %, 20 % and 30 %, and 10 % and 20 %) served as attention check items. Whether participants understood the concept of EV was measured with an open question and one item assessing whether EV was used in individuals' choices ("Did you make use of the expected value when making a decision?"; answer options: No and Yes).

Furthermore, four items assessed effort and perceived difficulty of the tax decision task (e.g., "The process was tiring." Likert-point scale from 1 = Fully Disagree to 5 = Fully Agree). Three items each from the subscale "Commitment" and "Game playing" of the Motivational Postures scale (Braithwaite, 2003) measured attitudes towards tax paying. Finally, we included technical checks (e.g., self-reported device use, operating system, screen resolution) and demographics. We excluded participants who participated using a smartphone or tablet device (it was made mandatory in the instructions and on the Prolific platform to use a desktop or laptop computer). This was measured with one item where participants self-stated the used device (e.g., laptop) and input device (e.g., computer mouse). Additionally, device and browser information were extracted using Javascript. We excluded participants who self-reported technical problems during the task and failed to get 50 % of each block of the manipulation check items correctly. Exclusion criteria were preregistered.

At the end of the study, one decision of the lottery task (min = £0.03, max = £1.10) and one of the tax rounds (conversion rate: 350 ECU = £1; min = £0.70, max = £4.00) were randomly drawn and paid out. Mean payout was £6.58 (*SD* = 0.83, min = 3.83, max = 8.10) including a guaranteed participation fee of £3.00.

2.3. Data preparation and processing

As suggested by Payne et al. (1988), we discarded events with acquisition times under 100 ms, assuming that such short acquisitions cannot be processed consciously. In sum, the 345 participants made 8,280 decisions in the experiment, preceded by 70,093 box openings. Opening times were log-transformed for the process data analysis to get a distribution closer to a normal distribution (e.g., Schulte-Mecklenbeck et al., 2013).

3. Results

The results section is divided into two parts. In line with the order of our hypotheses, we first present the analysis of the behavioral data, followed by the analysis of the process data. Where appropriate, exploratory findings are additionally reported and explicitly labeled as such (i.e., not preregistered).

3.1. Behavioral data analysis

We first descriptively examine to what extent compliance decisions were in line with the predictions of the deterrence model. Risk-neutral individuals should evade taxes in all rounds, given the calibration of parameters. Thus, comparing the between-subject conditions, greater model conformity is expressed by a higher proportion of evasion. As illustrated in Fig. 2, mean compliance was lowest

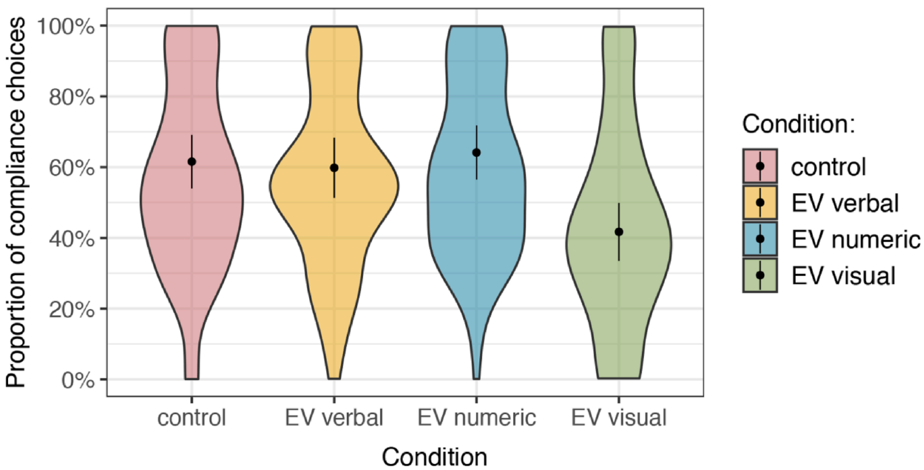

Fig. 2. Average per person compliance proportions over the 24 choices between the four conditions.

in the visual cue condition (41.7 %, SD = 4.2 %), followed by the verbal condition (59.8 %, SD = 4.3 %), the control condition (61.6 % SD = 3.9 %), and finally the numerical condition (64.1 % SD = 3.9 %). To test whether choices were generally more model-conform when explicit EV information was provided (H1), we conducted a generalized linear mixed-effects model with compliance (binary; full evasion vs. full compliance) as the outcome variable and a fixed effect that compares the control condition against all three EV conditions combined (Supplementary Table S1, Model 1). We included a random intercept for participants to account for the repeated measures structure (this specification applies to all reported models). Against the predictions of the deterrence approaches, there was no overall significant difference in compliance between the control condition and the three conditions where we provided explicit EV information (OR = 0.77, 95 % CI [0.52, 1.13], p =.186).

We then entered the four conditions separately (dummy coded with control as the reference group) to test whether each of the three EV conditions was different from the *control condition* (Supplementary Table S1, Model 2). Additionally, we inspected planned contrasts to see whether the three EV conditions led to different degrees of model conform decisions. Because the presented EV formats differ in the degree of complexity, we assumed that a visual cue would be most effective, followed by a numerical cue, and with a mere verbal explanation of EV being least effective (H2). Against this prediction, the proportion of compliance choices in both the numerical condition (OR = 1.12, 95 % CI [0.70, 1.77], p =.639) and verbal condition (OR = 0.93, 95 % CI [0.58, 1.50], p =.765) did not differ from the control condition. However, in line with our prediction, compliance in the visual cue condition was significantly lower than in the control condition (OR = 0.45 [0.28, 0.71], p <.001). The planned contrasts supported the inference that only the visual cue condition was different from the former three conditions (control: OR = 2.24 [1.22, 4.12], p =.004; verbal: OR = 2.08 [1.10, 3.95], p =.017; numerical: OR = 2.50 [1.34, 4.66], p <.001) in terms of lowered compliance rates (Fig. 2 and Supplementary Table S2). Controlling for risk preference, attention and comprehension checks, and self-reported use of EV information did not substantially influence the qualitative interpretations of these results. As can be expected, both risk measures were associated with compliance (i.e., higher risk preference predicts more evasion) but no interactions with the experimental conditions were observed. There were also no effects when including the two different blocks of manipulation checks. With regard to self-reported EV use, participants who indicated that they considered the EV in their decision were less compliant, and this was the case in all conditions (see Supplementary Table S3a and S3b).

Fig. 3 illustrates the estimated compliance proportions by condition for each level of the four tax parameters. Inspecting the effects of changes in the tax-related parameters, we ran four generalized linear mixed effects models to investigate which factors influenced tax compliance decisions. We entered conditions and their interaction with the tax-related factors (income, tax rate, audit probability, and fine rate) as fixed effects (all dummy coded; Supplementary Table S4). As predicted by the deterrence approach, there were significant positive simple effects of audit probability (20 %: OR = 4.47, 95 % CI [3.39, 5.88], p <.001; 30 %: 37.48, 95 % CI [26.63, 52.74], p <.001) and fine level (OR = 1.99, 95 % CI [1.64, 2.42], p <.001), suggesting a clear deterrent effect of audit probability and fine level on compliance. The only significant interactions were the ones between the audit probability dummies and the *EV* numerical condition (20 %: OR = 1.96, 95 % CI [1.29, 2.97], p =.002; 30 %: OR = 1.87, 95 % CI [1.12, 3.14], p =.017), suggesting that increases in audit probabilities had a slightly more deterring effect in the *EV* numerical condition. There was no significant interaction effect of fine rate, suggesting that an increase in the fine rate from 0.5 to 1 had a comparable relative effect in all conditions.

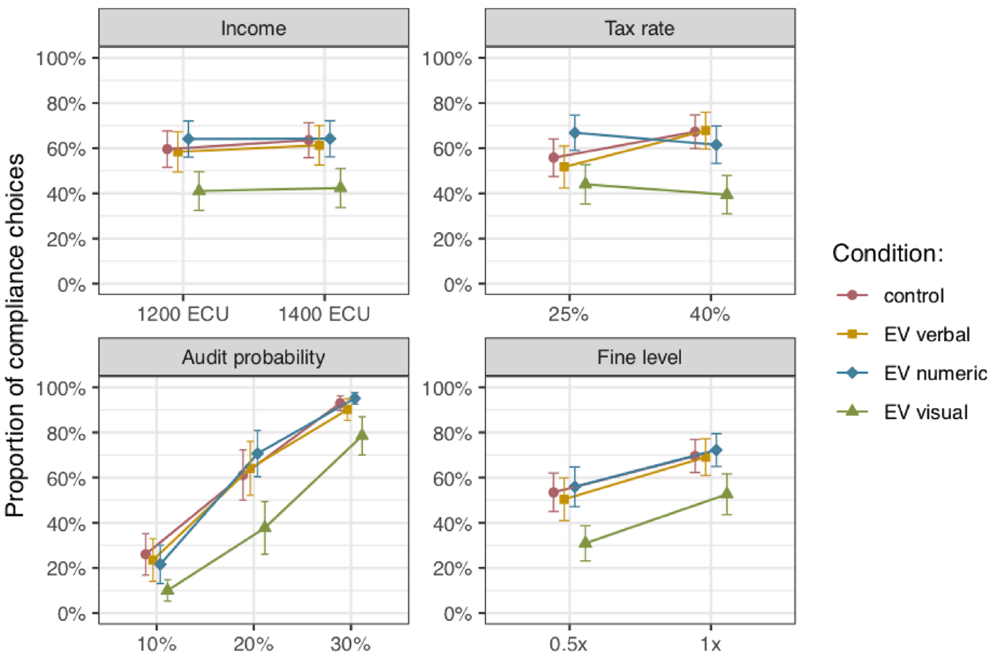

Fig. 3. Interaction effects of income, tax rate, audit probability, fine level, and experimental condition.

We observed a significant positive simple effect of tax rate ($OR = 1.63$, 95 % CI [1.34, 1.98], $p < .001$). Additionally, the negative interaction effects of the two EV conditions with tax rate express that tax rate had a negative effect in the numerical condition ($OR = 0.49$, 95 % CI [0.37, 0.64], $p < .001$) and visual EV condition ($OR = 0.51$, 95 % CI [0.38, 0.67], $p < .001$). Thus, when an explicit EV cue was provided, higher tax rates were associated with less tax compliance as predicted. Finally, different income levels had no significant effect on tax compliance ($OR = 1.18$, 95 % CI [0.98, 1.43], $p = .084$).

Next, we explored the decision dynamics throughout the experiment. Fig. 4 shows compliance proportions for every round of the experiment. The rounds in this figure are ordered by an increasing expected rate of return from evasion relative to compliance from left to right. This means that the monetary attractiveness of tax evasion increases from left to right. Consequently, model conform decisions, irrespective of the risk preferences in our sample, would be expressed by a flat or monotonically decreasing slope from left to right. However, as evident from the figure, the decrease was non-monotonic, with some rounds where compliance seemed to spike in reaction to the high audit probability. Most notably, this can be observed when we compare the rounds with an expected return of 0.27. While in the two rounds that were characterized by a high tax rate (i.e., 40 %) and high audit probability (i.e., 30 %) compliance was at the highest level, in the two rounds with a low tax rate (i.e., 25 %) and low audit probability (i.e., 10 %) compliance was at a low point.

Fig. 4 shows a pattern where in the numerical condition more participants chose compliance when the expected return for evasion (i.e., the numerical difference between “Expected Value: Don’t Pay Tax” relative to “Sure Outcome: Pay Tax”) was relatively low. Conversely, in the visual EV condition with higher expected returns for evasion, participants chose evasion more often. We ran a generalized mixed effect model with tax compliance as the dependent variable and entering condition and the interaction with expected returns for evasion as fixed effects to reveal whether this difference is significant.

Looking at the numerical condition against the control condition while holding the expected return of evasion over compliance constant, we observe that participants in the numerical condition were generally more compliant ($OR = 3.63$, 95 % CI [1.87, 7.02], $p < .001$). However, with increasing expected rate of return, individuals in the numerical condition became increasingly less compliant than those in the control condition, indicated by a significant negative interaction effect between the numerical condition and the expected return of evasion variable ($OR = 0.03$, 95 % CI [0.01, 0.10], $p < .001$). As established earlier, this results in an overall null-effect for the difference between the control condition and the numerical condition. Deviating from this pattern, in the visual cue condition compliance proportions were not different from the control condition when holding the expected return of evasion constant ($OR = 1.05$, 95 % CI [0.45, 2.03], $p = .882$), however, compliance then significantly decreases with increasing expected return of evasion, ultimately to the lowest compliance level ($OR = 0.05$, 95 % CI [0.02, 0.17], $p < .001$). This decrease in rounds with higher expected rates of return drives the overall effect of condition (H2).

To summarize the behavioral results, we found that compliance is much higher than the model predicts across all conditions. Although explaining EV and presenting it with a visual cue led to more model conform decisions compared to the other conditions, compliance is still significantly above the full evasion prediction of the deterrence model. Further explorations based on the tax parameters suggest that participants overweight single salient deterrence parameters (i.e., audit probability and fine rate). Additionally, participants seem to have failed to consider that the fine is proportional to the evaded tax. Providing an explicit EV cue seems to correct for this misperception, but only in rounds with a high expected return of evasion. When the expected return of evasion was low, presenting the EV as a numerical cue led to even higher tax compliance, resulting in an overall null-effect of the numerical condition.

3.2. Process data analysis

Next, we investigate underlying cognitive processes of the behavioral condition differences. We first descriptively explored how frequently and for how long each information box was attended to, in which order the information was attended (first acquisition and last acquisition), and whether there were recurring transitions between information boxes that suggest EV-like calculations (see Fig. 5). To provide a more detailed and meaningful overview, we grouped the acquired information by experimental condition and decision phase (first half = exploration phase, second half = choice phase).

The box opened first most frequently was income in all conditions (30.7 % verbal condition; 26.7 % numerical condition; 31.4 % visual cue condition) besides the control condition, where the tax rate was acquired first most often (33.9 %). The last box opened before the final decision, was income (31.1 %) in the control condition, audit probability (28.8 %) in the verbal condition, “Sure outcome: Pay tax” (48.6 %) followed by “EV: Don’t pay tax” (34.6 %) in the numerical condition, and the visual cue (80.2 %) in the visual EV condition.

In both the verbal condition and the control condition, participants obtained information about the four tax parameters. However, in the verbal condition, we additionally explained how to integrate this information to calculate the EV in each tax round. Accordingly, we expected more box openings and longer acquisition times in the verbal condition, indicating such calculations (H3a). Additionally, we expected more transitions between audit probability and income as well as between audit probability and fine (i.e., EV-like transitions) in the verbal condition compared to the control condition (H3b). We regard such transitions as indicative of EV-like transformation processes that should result from the provided EV explanation.

The icon graph suggests that participants in the verbal condition made transitions between audit probability and fine in the first half of the decision phase and that they also had more attention on audit probability and fine in the second phase of the decision phase. Participants might have attempted EV-like calculations after explaining how to do so, although we find no behavioral effect between the verbal condition and the control condition in terms of more model-conform decisions (i.e., evasion). To test this observation, we ran two linear mixed-effects models with frequency of box openings and log acquisition time as dependent variables and a fixed effect to compare the control condition against the verbal condition (Supplementary Table S5). Against our predictions and in contrast to what the icon graph visually suggests, both models show no difference in box openings or acquisition times between the two groups

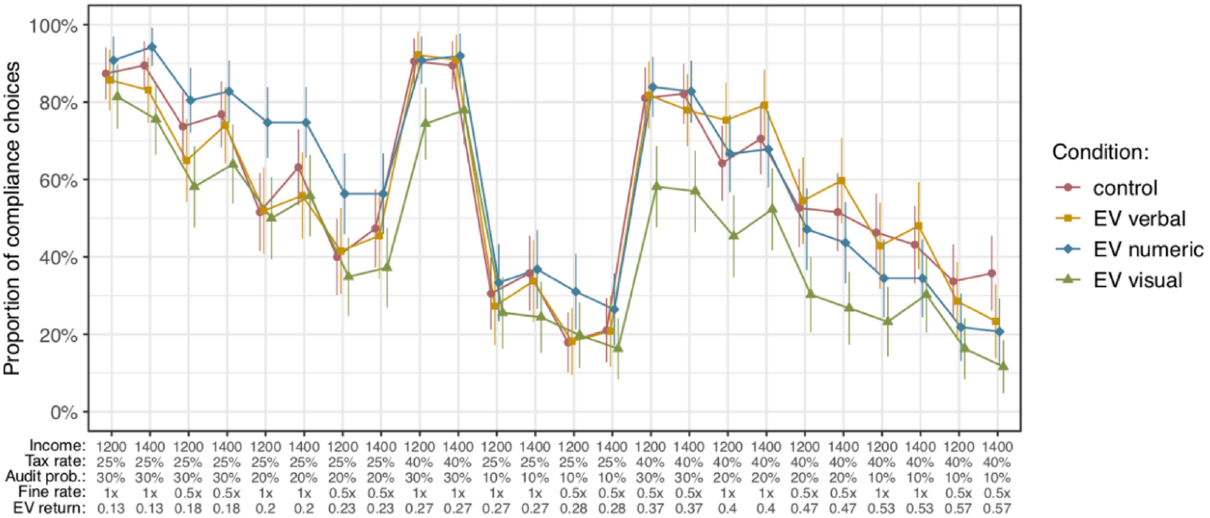

Fig. 4. Proportion of compliance choices plotted over the 24 rounds.

Note. Rounds are ordered from left to right by increasing expected rate of return from evasion relative to compliance. This was not the order of presentation in the experiment and only serves illustrative purposes. See Supplementary Fig. S1 for a figure with a continuous x-scale and fitted regression lines.

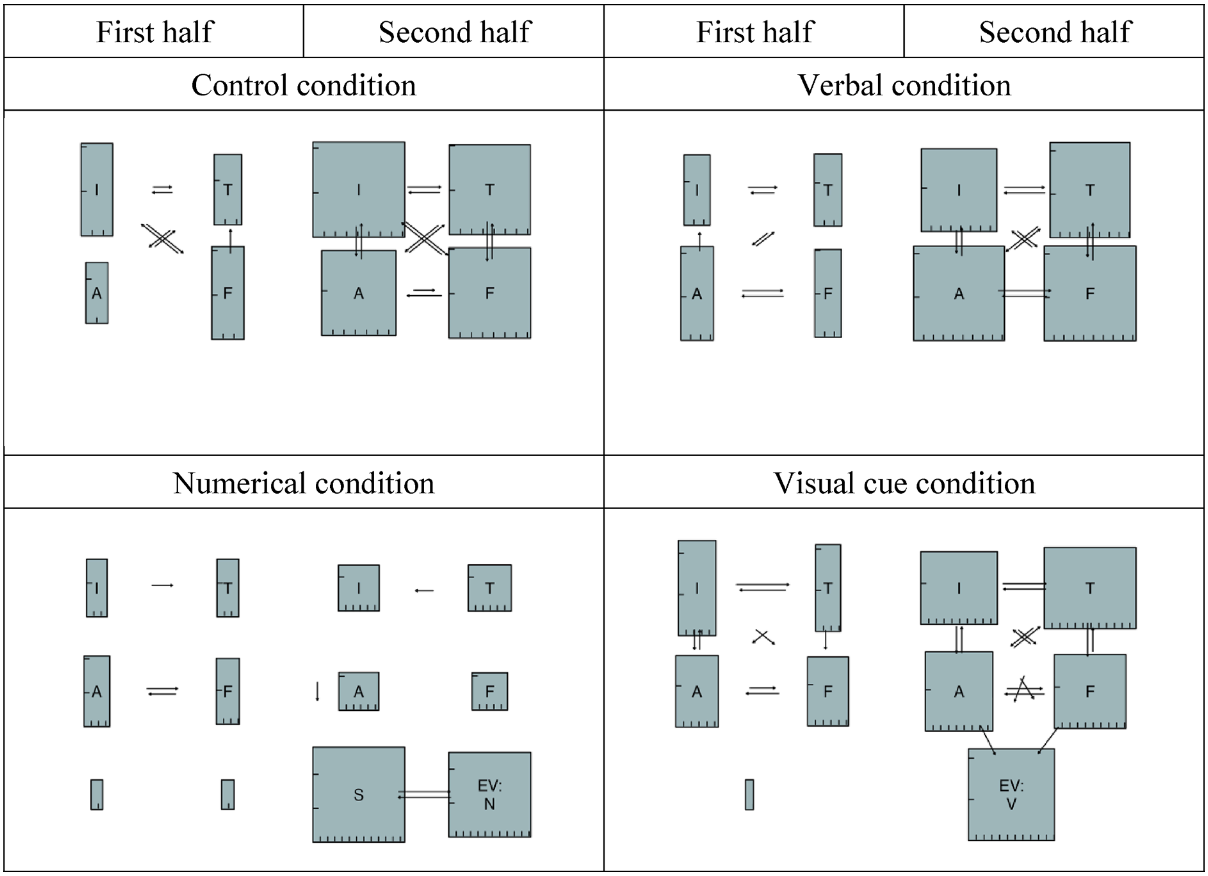

Fig. 5. Icon graph of the observed process data by condition and decision phase Note. I = Income, T = Tax due, A = Audit probability, F = Fine, S = Sure outcome: Pay tax, EV: N = EV: Don't pay tax, EV: V = EV: visual. The rectangle height shows the average frequency of acquisition and the width the average 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 0.33 per trial are not displayed for clarity.

(frequency: $B = 0.30$, 95 % CI [−0.52, 1.12], p =.468; log time: $B = 0.01$, 95 % CI [−0.29, 0.31], p =.955; see also Fig. 6a).

Additionally, we conducted two linear mixed-effects models with the existence of probability-income-transitions and probability-fine-transitions (Supplementary Table S6) as dependent variables and a fixed effect to compare the verbal condition against the control condition. Both models indicate that participants did not make more EV-like transitions in the verbal condition (probability-income-transitions: $B = 0.02$, 95 % CI [−0.09, 0.14], p =.705; probability-fine-transitions: $B = 0.04$, 95 % CI [−0.25, 0.34], p =.774) compared to the control condition, suggesting that the verbal instruction did not significantly influence key process metrics that would be diagnostic of EV-like information acquisition.

Next, we investigated the ease of information processing between the different EV conditions (verbal, numerical, and visual) in terms of decision times as well as the number of box openings. As the visual EV cue should be easier to process than the numerical EV cue and acquiring the EV information is easier than calculating it by oneself, we expect less attentional weight (i.e., fewer box openings and shorter acquisition times) on the tax parameters in the visual EV condition followed by the numerical condition and the verbal condition (H4). For this purpose, we ran two linear mixed-effects models with relative frequency of box openings (box openings in total divided by the displayed number of boxes in the condition) and log acquisition time as dependent variables and a fixed effect to compare the visual EV condition and numerical condition against the verbal condition (Supplementary Table S7).

Results for the relative frequency of box openings support this assumption only for the numerical condition where participants had significantly fewer box openings compared to the verbal condition ($B = -0.34$, 95 % CI [−0.54, −0.14], p <.001). The difference between the visual EV condition and the verbal condition as well as between the visual EV condition and numerical condition was not significant. Contrary to our assumption about decision times, log acquisition time was significantly higher in the numerical condition compared to the verbal condition ($B = 0.37$, 95 % CI [0.10, 0.63], p =.002). Again, the difference between the visual EV condition and the verbal condition ($B = 0.19$, 95 % CI [-0.08, 0.45], p =.167) was not significant.

Finally, we compare the visual cue condition with the numerical one to investigate our prediction that a visual EV cue should be easier to process than a numerical one. Therefore, we tested whether participants in the visual EV condition put less emphasis on the four tax-related boxes expressed by a higher proportion of attention to explicit EV information compared to the numerical condition (H5). Since the number of boxes was different between the two conditions (i.e., five for the visual EV condition and six for the

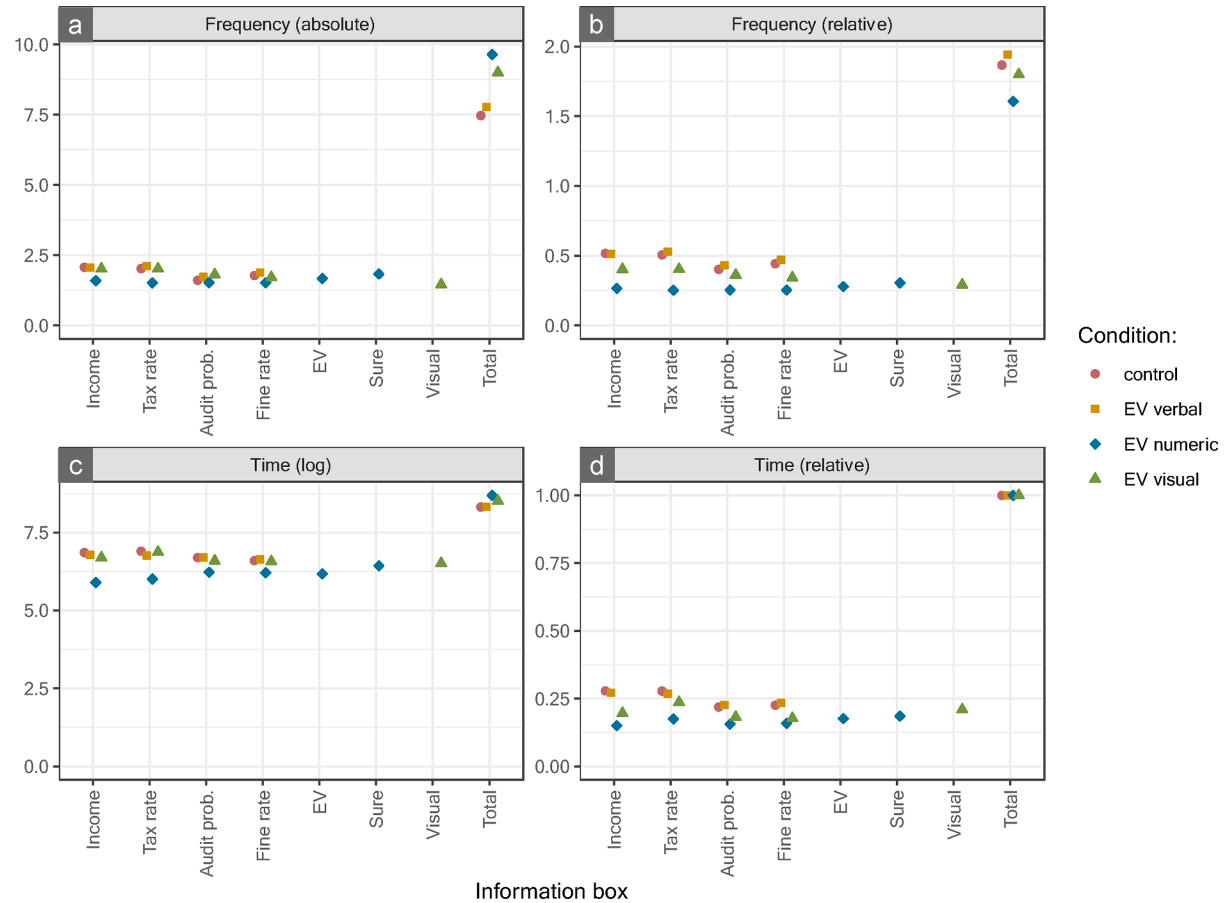

Fig. 6. Acquisition frequency and time for the information boxes Note. Process data of all information boxes are plotted over (a) absolute frequency of box openings, (b) relative frequency of box openings given the design (box openings in total divided by the displayed number of boxes in the condition), (c) log acquisition time, and (d) relative acquisition time in ms (acquisition time in total divided by total time).

numerical condition), we used relative box openings and acquisition times. We conducted two linear mixed-effects models with relative frequency of box openings and relative time spent on the EV information box(es) as outcome variable and a fixed effect to compare the visual EV condition against the numerical condition. Against our prediction, participants opened the EV box relatively less frequently ($B = -0.19$, 95 % CI [−0.23, −0.16], $p < .001$) and spent relatively less time acquiring information presented in this box ($B = -0.15$, 95 % CI [-0.19, −0.10], $p < .001$) compared to the numerical condition (Supplementary Table S8).

Further, we explored whether the amount and duration of acquired information are indicative of tax compliance decisions. Supplementary Table S9a and S9b present the results of four mixed-effects models (since the number of presented boxes differed between the groups) with frequency and log duration of box openings as fixed effects, respectively, and compliance (binary, i.e., full evasion vs. full compliance) as dependent variable. The results reveal for the control condition that frequency ($OR = 1.23$, 95 % CI [1.10, 1.37], $p < .001$) and duration ($OR = 1.13$, 95 % CI [1.02, 1.26], $p = .018$) of income predicted higher compliance, while frequency of tax rate ($OR = 0.84$, 95 % CI [0.75, 0.94], $p = .002$), frequency of fine ($OR = 0.88$, 95 % CI [0.78, 0.99], $p = .030$), and duration of audit probability ($OR = 0.70$, 95 % CI [0.58, 0.84], $p < .001$) were predictors for lower compliance. Results for the verbal condition were similar as frequency of income ($OR = 1.13$, 95 % CI [1.01, 1.26], $p = .036$) was a predictor for higher compliance and frequency of tax rate ($OR = 0.89$, 95 % CI [0.80, 0.99], $p = .040$) and fine ($OR = 0.86$, 95 % CI [0.76, 0.97], $p = .016$) predicted lower compliance. However, duration did not predict compliance for any of the tax parameters in this condition. For the numerical condition, the attention on “EV: Don’t pay tax” (frequency: $OR = 0.49$, 95 % CI [0.43, 0.56], $p < .001$; duration: $OR = 0.79$, 95 % CI [0.74, 0.85], $p < .001$) predicted lower compliance. Respectively, attention on “Sure outcome: Pay tax” (frequency: $OR = 2.20$, 95 % CI [1.92, 2.52], $p < .001$; duration: $OR = 1.33$, 95 % CI [1.23, 1.44], $p < .001$) predicted higher compliance. For the visual EV condition only duration on the visual cue itself predicted lower tax compliance ($OR = 0.83$, 95 % CI [0.77, 0.91], $p < .001$).

In an additional step, we explored the relation of participants risk-preference and information acquisition patterns. Overall, we do not find that risk-preference is associated with frequency of information acquisition (i.e., more box openings) (OR = 0.09, 95 % CI [-0.06, 0.24], p =.261). However, we do observe that risk-preference predicts duration of information acquisition (OR = 182.19, 95 % CI [18.47, 345.92], p =.029),[7] indicating that participants who are more risk averse acquire information longer than risk-seeking participants. However, we do not find any evidence of respective differences between conditions and also no relation of risk-preference and information acquisition patterns within our experimental conditions, maybe also due to statistical power.

To summarize the process data results, we first compared the verbal condition with the control condition to investigate whether explaining the EV resulted in more acquisition behavior indicative of EV-like calculation efforts. Although visual inspection of the icon graph indicates that participants in the verbal condition might have attempted to make EV-like calculations, we found no significant differences in acquisition frequency, acquisition time, and EV-like transitions between these two conditions. Second, we compared the three conditions where EV information was provided (i.e., verbal, numerical, visual cue) in terms of ease of information processing. While we found some differences between conditions in the relative amount of box openings and decision times, they do not suggest that one way of presenting EV information was easier to process than the others. Finally, we compared the visual cue condition with the numerical condition, in terms of a higher proportion of attention to the EV cue and found, against our predictions, relatively less emphasis on the visual cue than on the numerical cues.

4. Discussion

According to traditional economic theory, individuals are expected to consider all relevant information and maximize their expectations, ultimately choosing the option with the highest subjective gain (i.e., the highest EV or EU). Even assuming bounded rationality, we should expect that individuals at the latest adjust their preference when they are provided with explicit EV information. In a previous study (Kogler et al., 2022), we found that after verbally explaining the concept of EV and providing explicit numerical information on the EV in each decision round, participants did not make more model-conform decisions. The goal of the present study was to test the robustness of this finding and whether it is generalizable beyond a mere numerical presentation of EV.

In the present study, we varied how EV information was conveyed to participants to systematically investigate whether individuals consider EV information in tax decisions when such information is made accessible and comprehensible and how the availability of EV information potentially alters the decision-making process. According to our predictions, participants made more model-conform decisions (i.e., evasion) when we first verbally explained the concept of EV and then explicitly provided EV information with a visual cue indicating whether evasion is likely to pay off. However, the condition with verbal information only and with additional numerical EV information did not influence compliance behavior compared to the control condition, which is in line with our previous study (Kogler et al., 2022).

Although it seems that the visual EV cue helped participants to adjust their preferences in line with the deterrence approach, compliance did not drop below 40 %, revealing that even in a highly artificial setting, deterrence alone can hardly explain tax compliance decisions. An obvious argument against this conclusion could be that (some) participants simply did not understand the task, the explanation of the EV or some other feature of the experiment influenced their preferences. However, this seems unlikely for the following two reasons: First, a high average compliance rate in tax evasion games is not a particularly surprising finding. Alm and Malézieux (2020) report in a meta-analysis an average compliance rate of 65 % ($SD = 41$ %) across experimental studies, which is slightly higher than the average compliance rate of 62 % ($SD = 4$ %) we observed in the control condition ($M = 54$ %, $SD = 2$ % across

[7] These analyses are based on the incentivized risk measure (Holt & Laury, 2002), which is highly correlated with the self-report risk measure (Dohmen et al.) in our study.

all conditions). Second, analyzing the manipulation check items confirmed that the observed deviations from the standard economic model can hardly be explained by a lack of understanding of the provided explanation of the concept of EV and how such information can be used to optimize decisions from a purely financial perspective.[8] We interpret these findings as strong support for the claim that non-monetary factors play an important role in tax compliance decisions. In line with a prominent strand in the literature, it is likely that ethical considerations (e.g., fairness perceptions, tax morale), individual attitudes and social norms, or trust in governmental authorities substantially contribute in such decisions (e.g., Braithwaite, 2003; Kirchler, 2007; Torgler, 2002; Wenzel, 2004).

Analyzing the process of information acquisition revealed that providing explicit EV information had an influence on the attention to specific information and resulted in some differences between the conditions. However, we find no evidence indicating that one way of presenting EV information was easier to process. Considering the differences between the two ways of conveying additional EV information, we found that participants put less relative emphasis on the visual cue than on both numerical cues. If we consider that salient elements are generally fixated first (Peschel & Orquin, 2013), more frequently, and longer (Lohse, 1997; Milosavljevic et al., 2012), this indicates that the behavioral effect in the visual cue condition cannot be explained exclusively by salience.

If neither simplicity nor salience seems to be the main drivers of the conditional effect, what else could explain the substantial difference in compliance in the visual cue condition? It is likely that the visual cue, the stylized highlighting of one option, had a stronger demand character (see demand effect; Bardsley, 2005; Zizzo, 2010) than the numerical cue or the verbal explanation of EV. Given that a clear indication (i.e., pointer) on what option to take was provided, participants may have been especially sensitive to this cue to "solve" the unfamiliar and potentially complex task at hand. Additionally, drawing attention to the experimental variable of interest (i.e., model-conform decision indicated by the EV) may have changed participants' behavior. However, the absence of an effect in the verbal explanation and numerical cue condition indicates that a potential demand effect is limited to the visual cue condition. Nevertheless, although this visual cue may have made the correspondence between monetary incentives and model-conform behavior more salient (i.e., evasion pays off; see Binmore et al., 1985; Zizzo, 2010), participants still decided against this cue in 40 % of their decisions. This clearly supports the conclusion that deterrence considerations do not sufficiently predict tax behavior and that compliance is the normatively expected behavior even in rather artificial lab experiments (see also Bruttel & Friehe, 2014).

Inspecting the icon graph indicates that participants who received an explanation of the EV prior to the experiment might have attempted to make EV-like calculations. However, regression analysis reveals no difference between the two conditions without explicit EV information in terms of frequency and duration as well as transitions indicative of EV-like calculations. These exploratory analyses suggest that when no explicit EV information was provided, more attention on audit probability and fine was associated with higher tax evasion rather than having a deterring effect, as suggested by the analysis of the tax parameters. However, the causal link here is ambiguous. It might either indicate that those individuals who emphasized the deterrence factors did come to more model-conform decisions or participants who had already the intention to evade paid more attention to the deterrence information. Similar to our previous study (Kogler et al., 2022), participants that showed more attention to the additional EV information provided in the numerical condition and the visual EV condition made more decisions that were congruent with the respective indicated information (i.e., evasion for "EV: Don't pay tax" and the visual cue; compliance for the "Sure outcome: Pay tax"). Although, this did ultimately only lead to more model-conform decisions in the visual cue condition.

Nevertheless, even when explicit information on calculating the EV was provided, most participants did not attempt such calculations, let alone adjust their choices accordingly. Such evidence is in line with relevant JDM literature showing that explicit EV information does not necessarily result in choosing gambles with higher EVs (see, for example, Li, 2003; Lichtenstein et al., 1969). Although EV and EU models are generally good predictors for decisions in multiple-play experiments, single-play situations seem to favor more heuristic approaches (Colbert et al., 2009; Li, 2003). This should apply to tax compliance decisions that are by nature single-play situations,[9] even more in the real-world context. For instance, (Blaufus et al., 2013) investigated whether changes in the tax rate and the tax base increase the perceived tax burden and found that most participants used decision heuristics. Even after introducing participants to a learning environment, rational choices did not increase considerably.

An obvious question in this context is what cognitive heuristics may better explain our data. Although we believe this is a promising avenue for future studies, this first requires further investigation of the relation and comparability of simple gambles and tax decisions. For instance, tax decisions focus primarily on the loss domain, are more complex, and often entail additional context factors like fairness and norm considerations (for a detailed discussion, see Kogler et al., 2022). Most importantly, the information matrix in a classical tax evasion game (i.e., income, tax rate, audit probability, and fine) is structurally different from the simpler outcome-probability presentation of multiple gambles in a typical JDM experiment. However, commonly used indices in the JDM literature like the Search Index (SI; Payne, 1976), Strategy Measure (SM; Böckenholt & Hynan, 1994, and Systematicity of Search Index (SSI; Perkovic et al., 2018) are based on a comparison of alternative-wise (i.e., transitions between gambles) and attribute-wise (i.e., transitions between probability and outcome) search which is not directly applicable to the information matrix we applied based on the typical tax evasion game.

One surprising finding of a previous related study (Kogler et al., 2022) was the observation that explicit numerical EV information

[8] Note that we extensively evaluated all explanations of the key concepts in the introduction and pre-tested it beforehand.

[9] Note that by incentivizing based on one randomly chosen single round and not an average over all rounds, perceptions of independence of single decisions should have been highlighted in our study (see Laury, 2005).

resulted in more compliance when evasion was attractive. Three different mechanisms were suggested that could potentially explain this unexpected result: a misunderstanding of EV, the normative labeling of one choice option, and an anchoring effect.[10] As outlined before, participants in the present study had a sufficient understanding of the task, tax parameters, and EV concept. Further, we accounted for potentially loaded wording of the choice options, which could elicit stronger norm obedience (for example see, (Baldry, 1986; Mittone, 2006), by using more neutral labels (i.e., "Expected Value: Don't Pay Tax" and "Sure Outcome: Pay Tax"; not mentioning the word evasion). Concerning a potential anchoring effect (Tversky & Kahneman, 1974), we did not find a significant difference in compliance between the respective two conditions in this study. However, descriptively we still observe a tendency for more compliance when we provide numerical EV information. However, categorizing rounds in terms of expected return from evasion, we found that when the difference between the EV of evading tax relative to the sure outcome of paying tax was small (i.e., lower expected return for evasion), tax compliance in the numerical condition was higher. This effect reversed in rounds with high expected returns for evasion, effectively canceling out the overall effect. In the visual cue condition, compliance also decreased with increasing expected return for evasion but was not different from the control condition for rounds with lower expected return for evasion. This resulted in the only significant main effect of condition. As the visual cue cannot be affected by such an anchoring effect, the reversal of the effect in the predicted direction can be seen as support for the proposed potential anchoring effect. In other words, by presenting the EV as a numerical cue, we might have made it more salient when the combination of tax parameters led to a low difference between the sure outcome of paying and the risky outcome. If the potential added value of taking a risk was only small, then participants might have felt inclined to settle for the sure outcome and avoid any risk, even if it was objectively small. We want to emphasize that comparing the two conditions (numerical vs. visual cue EV presentation) constitutes not a direct test of this potential anchoring effect. For instance, we cannot rule out other features of the visual cue being responsible for enhancing model-conform decisions, such as visual biases (Orquin et al., 2018).

Concerning the tax parameter effects, our findings are in line with previous research showing that both a higher audit probability and a higher fine rate have a deterrent effect on tax evasion, with the latter usually having a weaker impact (Alm & Malézieux, 2020). When looking at individual rounds, participants seem to overweight single salient deterrence parameters (i.e., audit probability and fine rate), an observation that aligns with the previous study results. We observed no income effects, which is not surprising considering that the empirical evidence from tax evasion games is ambiguous, and income is often reported to have no effect in the laboratory (Alm & Malézieux, 2020; Muehlbacher & Kirchler, 2016). We find a positive link with compliance regarding the tax rate, which is in line with theoretical predictions (Yitzhaki, 1974) but contradicts most empirical findings. For example, Alm and Malézieux (2020) reported that around 60 % of experiments found a negative relationship between tax rate and compliance. One possible explanation for the positive relationship could be that participants failed to consider that the fine is proportional to the evaded tax, resulting in a decrease in the return of evasion for rounds with a higher tax rate. Interestingly, providing an explicit EV cue seems to correct for this misperception, but only in rounds with a high expected return of evasion. The latter is not surprising since the overall effect was driven by the rounds that increasingly favored evasion as the model-conform choice.

4.1. Limitations

One obvious limitation of our study is that we do not investigate actual tax compliance in the real-world. In research on tax behavior, lab experiments have a long tradition as they provide often the only option to manipulate specific variables, study certain behavior under controlled conditions, or investigate individual choices. Despite their high internal validity, previous research has raised the issue of the external validity of tax compliance experiments in the lab (Elffers et al., 1992; Muehlbacher & Kirchler, 2016), and suggested the application of certain features such as a tax-framing (instead of neutral language), a public goods setting (with a redistribution mechanism of tax revenue), or effort tasks where money must be earned before filing taxes. While the present study – by intention due to its specific nature – is rather artificial with regard to some of these aspects, this should not challenge the observed findings. We believe that in a more realistic setting consideration of expected values (which of course are not explicitly indicated in real-life) will likely be even less pronounced. Other limitations are specific design features like the dichotomous choice between full evasion and full compliance only or the delay of feedback on when audits happen to the end of the experiment. Both of these design choices were necessary in the current setting, in order to enable the presentation of one single explicit value and to prevent occurrence of audits to interfere with our procedure. As all these design features have been applied in tax compliance experiments before, and considering the underlying rationale for these choices, we are optimistic that they do not pose a threat to our general conclusion. Finally, we cannot exclude that the application of MouselabWEB elicited unnatural information acquisition behavior in our participants, for instance due to feeling nudged to open all presented information boxes. While this is possible, it seems unlikely that such a demand effect would substantially decrease compliance decisions in line with expected values.

4.2. Conclusion

In general, our results confirm that the deterrence approach, only considering economic determinants, does neither sufficiently predict nor explain tax evasion even in situations where information on tax parameters is both explicit and strongly emphasized. We

[10] We speculated that the explicit EV information was perceived as the potential maximum outcome of evasion, rather than a long-term prospect of multiple outcomes, and thus, the difference between compliance and evasion was perceived lower (for an extensive discussion see, Kogler et al., 2022).

confirm our previous results that providing numerical EV information does not lead to more model-conform decisions and show that this effect is robust. By implementing a visual cue, model-conform decisions increase significantly; however, the process data is not indicative of what causes this effect. We argue that a potential anchoring effect might have suppressed the preference adjustment (i.e., compliance) with the suggested choice indicated by the provided EV information (i.e., evasion). Only the more comprehensible EV cue was able to make some participants adjust their preferences. However, even confronted with this accessible EV information, a significant share of decisions was still not conforming to the deterrence model. Consequently, we argue that our previous finding (Kogler et al., 2022) is not merely a result of participants not understanding EV calculations but suggests that such processes are not of primary concern in the first place. In the bigger picture, the present study can be interpreted as further evidence that taxpayers do not make decisions according to the principle of maximizing financial outcomes. Although purely economic factors (e.g., audits, fines) as well as social and psychological factors (e.g., social norms, fairness considerations) influence tax compliance decisions, their interplay seems to be more complex than classical economic theories like the Allingham and Sandmo model assume. Hence, to gain a better understanding of how taxpayers arrive at compliance decisions, these factors have to be studied in combination, and research should not exclusively focus on outcomes but especially consider cognitive processes, for instance to investigate whether the weight of economic factors in compliance decisions is dependent on the peculiarity of social and psychological information.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data, codebook, materials screenshots for all conditions, and R code are publicly available via https://osf.io/v56rn/.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.joep.2023.102679.

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