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„Can a visual expected value cue evoke standard tax behavior? Putting the Allingham and Sandmo Model to the test using MouselabWEB"

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The standard model of income tax evasion arose in the 1970s when Becker's (1968) economics-of-crime model was applied to tax compliance. Allingham and Sandmo (1972) and Srinivasan (1973) modeled the decision of tax compliance as one under uncertainty. While Srinivasan (1973) follows an expected value (EV) approach, where individuals are risk neutral and will choose any option that promises a better longterm expected outcome, Allingham and Sandmo (1972) assume diminishing marginal utility of income and risk aversion. Despite these differences, the models have in common that they reduce the tax decision to weighing few factors against each other, the factors being the total income, the tax rate, the audit probability and the fine. These factors yield two options for which individuals can decide – the sure option and the risky option. The sure option is determined by the tax rate and the income. If individuals comply to paying the full tax, the total income is reduced by the tax as a portion of the income (tax rate x income). The risky option entails two outcomes. If taxes are evaded, the individual benefits if the evasion is not detected. If the evasion is detected, the evaded tax has to be paid back in addition to a fine. The decision whether to comply to paying the tax or to evade the tax, is made by weighing the sure option against the risky option.

The Allingham and Sandmo (A&S) model has since its publication enjoyed great popularity and is still the most influential model in tax compliance research[1]. Two assumptions are implied by this approach: First, individuals form expectations using the given factors. Second, the threat of being detected (audit probability) and the prompting punishment (fine) are the only motivators to comply.

Enforcement through audits and fines serves as a tool for creating tax compliance for tax authorities all over the world. The chance of being detected is, however, oftentimes low. In 2015, for example, the Internal Revenue Service (IRS) reported an overall audit rate of 0.8 percent (Internal Revenue Service, 2016, as cited in Alm, 2019). Taxpayers should therefore, if they make decisions in the way Allingham and Sandmo predict, decide to evade frequently. Nonetheless, it is found that taxpayers are far more compliant with paying income taxes than the A&S model predicts (Alm, 2019; Alm et al. 1992; Andreoni et al. 1998).

The A&S model has been the basis for experimental design variables in many studies. Findings in these kinds of experiments do, however, not reflect the pattern of compliance that the model predicts. Alm et al. (1992) for example find that participants show more compliance than the model would predict. The effect of audits that should occur according to

[1] Srinivasan and Allingham and Sandmo developed their models around the same time without knowledge of the respective other paper. This paper will furthermore refer to the A&S model of income tax evasion, as it has received more attention in the tax literature over the years.

Allingham and Sandmo is clear: a higher audit probability leads to more compliance. While in many studies audits act, as predicted, to increase tax compliance (Kirchler et al., 2010), in some cases they do not elicit tax compliance behavior. In Slemrod et al.'s (2001) experiment for example, high income earners reported lower tax liabilities when informed about an upcoming audit. Alm and Malezieux (2020) highlight the interaction of audit probabilities and fines in their meta-analysis. They find that increasing fine rates work against higher audit probabilities in intensive margins, i.e. compliance from evaders. The higher the audit probability, the more negative is the impact of the fine rate on tax compliance.

The model has been criticized to take tax decisions too much out of the real-world context. Individuals may not reduce their decision to a simple gamble. Other behavioral aspects may come into play when deciding to pay taxes. According to Braithwaite (2003) there are different motivational postures that underly tax decisions, signaling the social distance an individual seeks between them and tax authorities. While Commitment and Capitulation reflect rather positive attitudes towards tax authorities, Resistance, Disengagement, and Game Playing are more distant and negative postures. Not only individual motivation has been stressed as an important factor for tax compliance, but also social norms seem to influence it (Wenzel, 2004). Kirchler et al. (2008) highlight the role of authorities with their slippery slope model. In this model tax compliance both depends on the power of authorities and the trust in them. High power of authorities results in the classic enforced tax compliance, but high trust yields voluntary tax compliance. Maximum trust in authorities makes variations in power irrelevant and vice versa in this model.

Apart from neglecting important real life contexts that may influence tax decisions, the model includes implicit assumptions about the decision making process that are typically overlooked in tax compliance experiments when only the outcome is measured. Kogler et al. (2020) contribute to filling this gap with a process tracing tax experiment. Using MouselabWEB (Willemsen & Johnson, 2011) they observed the pattern of information acquisition. All the relevant tax information (income, tax due, audit probability and fine) were provided on a computer screen in covered boxes that would only open and reveal the information as long as the mouse curser was over the box. Information about frequency, duration and order of information acquisition was obtained. They also included a between subjects measure where they compared the additional inclusion of precalculated EV of evasion and sure outcome. The data were analyzed in regard to the implicit assumptions that all the relevant information must be observed, and bits of information must be integrated rather than be looked at separately. It was found that deterrence parameters did influence tax behavior but are not integrated in the way the model suggests. While every relevant information was observed at least once in 95% of the decisions, a look at decision and information acquisition patterns suggests that decisions were not made based on EVs, but rather based on singular parameters. Participants seemed to focus on one parameter to make their decision while ignoring the interactions between parameters. First, decision patterns showed unstable preferences where at one point the compliance rate increased with increasing expected return of evasion instead of steadily decreasing. Second, patterns of information acquisition, that suggest the integration of pieces of information did not result in more model conform decisions. Third, giving explicit EV information along with an explanation of the concept did not increase model conform decisions. All in all, information processing does not fully seem to align with the A&S model and factors other than the EV seem to impact the decision.

Kogler et al.'s (2020) study extends research on EV integration in decision making. Prior studies have examined the role of EV in gamble contexts and found similarly that participants did not take the EV into account the way the model predicts (Colbert et al., 2009; Li, 2003; Liechtenstein et al., 1969). Li (2003) found, that making EV information explicit and explaining the concept, did leave a substantial number of decisions for the lower EV. Kogler et al.'s (2020) results are in line with this finding.

Although gambling decisions are in some ways similar to tax decisions, drawing conclusions for decision making in the tax domain from knowledge acquired through gambling research does not suffice. As Kogler et al. (2020) have highlighted, tax decisions deviate from gambling decisions in three important aspects. First, tax decisions happen in the domain of losses rather than gains. People are more likely to take risks when deciding in the domain of losses (Kahnemann & Tversky, 1979; Tversky & Kahnemann, 1981). With taxes, they decide between a certain loss (i.e. paying tax) and a loss that only happens with a certain probability (i.e. the probability of being detected), but is higher than the certain loss (i.e. a fine on top of the due tax). Second, decision complexity plays a role in the information acquisition (Fiedler & Glöckner, 2012; Glöckner & Herbold 2011; Schulte-Mecklenbeck et al. 2017). Tax decisions are decidedly more complex than gamble decisions. There is usually less information to be considered for decisions between gambles. Probabilities for winning are directly given, whereas for tax decisions, there are more factors (i.e. income, tax rate, audit probability and fine rate) that all need to be taken into account to finalize the decision. Decision makers also know about social norms and may take them into account, complicating the decision. Third, social desirability clearly indicates a normatively favored decision. There may be established tax behaviors in a society that influence tax behavior (Bruttel & Friehe, 2014). It is therefore important to conduct experiments in a tax context.

Process tracing with MouselabWEB

Process tracing can reveal what is a prerequisite to the assumption that people consider information in a certain way – that they actually pay attention to it. Measuring attention to pieces of information can be done in several ways, that are differently suited to the needs of a research question.

The process of information acquisition can be monitored using eye tracking, where fixations and saccadic movements are indicators of attention. Eye tracking methods can detect fast switches of attention to various subjects and measure short inspections. This is especially suitable for processes that involve intuitive decision making and rely on automatic processes (Glöckner & Herbold, 2011; Norman & Schulte-Mecklenbeck, 2009).

More suited for deliberate decision-making is process tracing with MouselabWEB (Willemsen & Johnson, 2011), a tool that records information acquisition using mouse curser movements. The information is presented on a computer screen, structured in a matrix of boxes, but hidden. It can only be viewed when the mouse curser is deliberately moved over one of the boxes. Said box will uncover and reveal its information contents. Once the mouse curser leaves the area of the box, it will immediately cover again, and the information can no longer be viewed until the curser is moved back over the box. Each closed box has a label indicating the information that can be found under it. The program records opening and closing times of the boxes. Thus information about total view time, frequency of acquisition and transitions between boxes can be obtained.

Extending the research

Kogler et al. (2020) provided first insights into the decision making process behind tax decisions. When only looking at the outcome, direct deterrence parameters did influence tax available information was integrated to form EVs. Process data show, that relevant information was attended, but decision patterns still did not align with an EV approach. Striking is also the finding, that even clearly indicating the exact EVs did not change participant’s decision behavior. The results of this study call for a replication with some adjustments to the design.

It could have been, that participants did not understand the concept of EVs even though they received an explanation. The explanation was a brief text explaining each of the given informations (i. e. income, tax due, audit probability, fine, and depending on the group sure outcome and EV of evasion). Giving a clearer, more detailed explanation may help people understand the information better.

Further, the EV information was given as a numerical information, indicating the amounts of sure outcome and EV of evasion, respectively. Participants were left with comparing these numerical informations to draw their conclusions. Any condition where the EV of evasion exceeded the sure outcome should have resulted in tax evasion according to the model. As there were not more decisions for evasion, maybe indicating the information in a numerical form was not enough. A clearer cue could lead to different results.

Lastly, the study used parameters that ensured that, within subject, the EV of evasion was either higher, lower, or the same in relation to the sure outcome. These conditions called, according to the model, for different choices. Lower or equally high EV of evasion would call for the choice of the sure outcome (under the assumption of risk averse participants) and higher EV of evasion would call for the choice of evasion. There is, however, one disadvantage in this design, namely that the payment required after an audit could exceed the income. As the study was incentivized, this could lead to a negative payment. Further, these parameters featured unnaturally high levels of tax rates (30% vs. 50%), audit probabilities (10% vs. 25% vs. 40%), and fines (100% vs. 300%). Tax experiments have often been criticized for drifting too far from real world conditions, where audit and fine rates are relatively low (Alm, 2019; Alm et al., 1992; Andreaoni et al. 1998). To address these concerns, the parameters should be adjusted.

The aim of the present study is to extend the present research on processes underlying tax decisions. First, it replicates Kogler et al.’s (2020) study, comparing tax decisions when EV was only verbally explained and when explicit numerical expected value information is added. Second, a visual cue condition is added, in which the ratio between sure outcome and expected value of evasion is indicated with a depiction as well as a control condition where no EV information is provided. Thus, I can investigate whether a clearer cue is needed to enhance model-conform decisions. Finally, more detailed step by step explanations of tax and expected value information are introduced and within subject factors are adjusted so that tax parameters do not deviate as much from real life conditions and to avoid negative payments.

Hypotheses

Based on between-subject comparisons I make prediction both on the outcome and on the information processing level. First, I would like to investigate, whether providing explicit EV information influences the decision. Second, I would like to address the question whether the EV information received influences the decision process. I tested the following hypotheses:

Outcome Hypotheses

H1: Decisions are more in line with the A&S model when the EV is presented and/or explained compared to when there is no EV information available.

H2: Different amounts of EV information leads to different degrees of A&S model conform decisions. A visual cue generates the biggest degree of model conform decisions, followed by a numerical cue and lastly by a mere explanation of EV.

Information Processing Hypotheses

H3: Presence of a verbal EV explanation influences the information acquisition process.

H3a: A verbal explanation of the EV leads to more extensive information search. This translates to more and longer box openings when the EV is verbally explained compared to when no explicit explanation about EV is given.

H3b: The verbal explanation also leads to more EV calculations. This shows in more transitions between audit probability and income as well as between audit probability and fine.

H4: The ease of information processing differs between conditions. A visual EV cue is easiest to process followed by a numerical EV cue. The verbal explanation of EV is hardest to process. This translates to the fastest decision time and smallest number of box openings in the visual cue condition, longer decision time and larger number of box openings in the numerical cue condition and the longest decision time and largest number of box openings in the verbal explanation condition.

H5: There is more relative attentional weight on the visual cue than on the numerical cue as the visual cue is easier to process. This translates to different proportional attention on the explicit EV information in the two conditions. Compared to the four classic tax related information boxes, there will be more relative attention to the visual cue box than to the numerical cue boxes.

Method

Participants

Based on the available monetary budget a sample size of 455 was targeted. A sensitivity power analysis in G*Power for a simple omnibus test with four groups was conducted and yielded a smallest detectable effect for power = 95% is d = .39, for power = 90% d = .35 and power = 80% d = .31. Due to higher of sampling costs, the actual sample size was smaller, thus, detectable effect sizes for sufficient power are larger.

A total of 397 participants were recruited via prolific. Prerequisites were UK nationality and a study approval rate of 97/100. Of those, 10 were excluded because they had participated more than once, 18 had technical issues or were using an unpermitted device, and 28 failed to correctly answer 50% of the questions of each check item block. The remaining sample were 345 participants (165 female, 180 male) with a mean age of 35.7 (SD = 13.0), ranging from 18 to 80 years. Of these 345 participants, 95 received the control questionnaire, 77 the verbal explanation of EV condition, 87 the numerical cue condition, and 86 received the visual cue condition.

Design and procedure

An online questionnaire included a repeated measures tax compliance section, risk aversion measurements, manipulation checks and a postexperimental questionnaire.

Tax compliance

Tax compliance was obtained using a repeated measures design with a dichotomous dependent variable tax compliance (full tax evasion vs. full tax compliance). Four within-subject factors were fully permuted, resulting in a total of 24 rounds: income (1200 vs. 1400 Experimental Currency Units (ECU), tax rate (25% vs. 40%), audit probability (10% vs. 20% vs. 30%), and fine level (evaded amount plus 50% fine vs. evaded amount plus 100% fine). The order of rounds was random for each participant.

Further, four between-subjects factors varied the presence or absence of EV information: (1) no EV cue was present (2) EV calculations were verbally explained before the experiment, but no explicit cue was present during the experiment (3) a numerical cue indicated the EV level on top of prior explanation (4) a visual cue indicated the relation between EV and sure outcome on top of prior explanation.

The information was presented using MouselabWEB. Information about income, tax due, audit probability and fine was hidden behind labeled boxes and could only be viewed when the mouse curser was moved over the box of interest. The order of how the boxes were arranged was randomly determined out of two possible orders in the first round and stayed constant over the experiment. A fixation cross (50 x 50 px) was presented between each round for two seconds. They could indicate their decision by either clicking the box ‘Pay tax’ or the box ‘Don’t pay tax’. Conditions 1 and 2 featured only the four classic tax information boxes described above. Condition 3 included another two boxes with numerical information about sure outcome and EV of tax evasion, resulting in a total of six information boxes. Condition 4 included one additional box with the visual cue comparing sure outcome and EV of evasion, resulting in a total of five information boxes (see Figure 1). The visual cue included a circle with a pointer indicating the relative size of the difference of EV and sure outcome. The farther to the right in the black gradient on the top half of the circle, the more beneficial is it to decide for evasion.

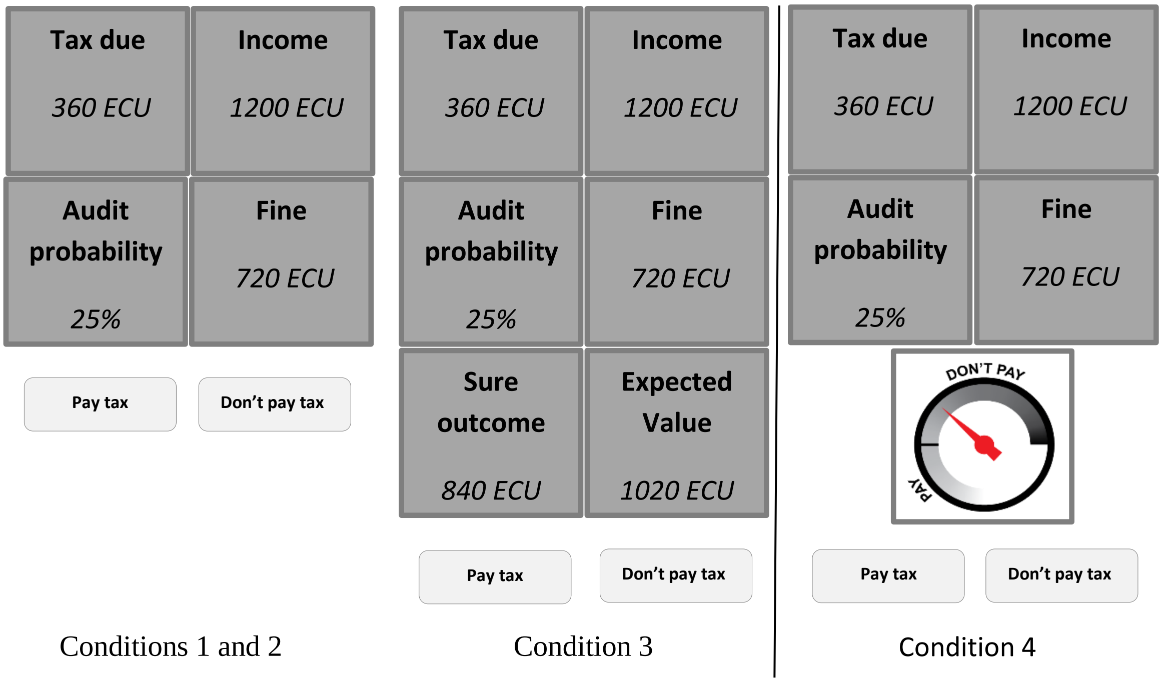

Figure 1. Information Matrices shown in the different experimental conditions
Note. The tax parameter information (e.g. 360 ECU) was hidden in the actual experiment and is shown here alongside the parameter label (e.g. Tax due) for presentational purposes only.

An explanation of tax parameters and EV (only in conditions 2, 3, and 4) preceded the tax compliance task. The explanation was adjusted to the experimental condition and used a box matrix resembling the one used during the MouselabWEB task. The information in each box was explained, first generally, then with an example. As condition 3 and 4 both featured boxes with EV of evasion information, the EV was explained by reference to the boxes. In condition 2, the EV was explained without reference to a specific box. Condition 1 only explained the four classic tax information boxes but featured no explanation of EV. Find examples of the EV explanations in Appendix A.

Participants were randomly assigned to one of the four conditions. The tax compliance task was incentivized. They were told at the beginning of the experiment that one of the 24 rounds would be randomly drawn and the respective amount would be paid at a conversion rate of 350 ECU = £1 at the end of the experiment. They received the payment from the tax compliance task (£1.71-£4.00) in addition to the lottery task payment (£0.03-£1.10) and the show up fee of £3.00. Mean payout was £6.58 (*SD* = 0.83, *min* = 3.83, *max* = 8.10).

Risk aversion

Two measures of risk aversion were included in the questionnaire. The first was a general question risk attitude question retrieved 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? (Likert-type scale from 1 = *Not at all willing to take risks* to 10 = *Very willing to take risks*). The other one was the Holt and Laury (2002) Lottery choice task. The first lottery choice was between Option A 200 ECU at 10% and 160 ECU at 90% and Option B 385 ECU at 10% and 10 ECU at 90%.

Manipulation Checks

Two manipulation checks were included, to test whether participants had understood the instructions and were paying attention during the experiment. The first check was pre-experimental and included four questions referring to an example of a tax compliance decision (income 1000 ECU, tax rate 300 ECU (30%), audit probability 10% and fine 600 ECU). Participants were asked questions like “How much would your remaining income be if you chose “Don’t pay” and there was no audit?”. The second check was post experimental and instructed participants to decide whether the statement was true or false, e.g. “The audit probability indicates the chance of a tax inspection taking place in the respective round” (true). Of a total of eight statements, five were about the EV of evasion and were therefore not included in condition 1.

Post experimental Questionnaire

The post experimental questionnaire included questions about the effort/the complexity of the experiment (e.g. “The process was tiring”; Likert-type scale from 1 = *Fully disagree* to 5 = *Fully agree*). Further, questions about the motivational postures of commitment and game playing (Braithwaite, 2003) were presented (e.g. “Paying my tax ultimately advantages everyone”, and “I enjoy exploring the gaps and barriers of tax law”, 1 = *Completely agree*, 2 = *Disagree*, 3 = *Neutral*, 4 = *Agree*, 5 = *Completely agree*). Lastly, participants were asked whether they knew what an EV is and whether they used it in the experiment, whether there were any distractions and whether they could concentrate during the experiment, what type of device they used to complete the questionnaire, and about their sociodemographic data.

Find more information on the materials in Appendix A.

Preparation of MouselabWEB Data Events with acquisition times under 100ms were discarded as suggested by Payne et al. (1988) as these are assumed to be too short to be consciously processed. A total of 70093 box openings (*mean* = 8.47) preceded the 8280 decisions made during the experiment. To closer resemble a normal distribution, box opening times were log-transformed as is common practice (e.g., Schulte-Mecklenbeck et al., 2013).

Results

The results section is divided in two parts. First it will look at the outcome hypotheses and then at the process hypotheses.

Outcome Hypotheses

Hypothesis 1 concerned the presence of EV information in any form, as an explanation before the experiment or as numerical or visual cue during the experiment. Presence of EV information was expected to lead participants to more A&S model conform decisions, decreasing the tax compliance. To test hypothesis 1, a logistic regression with tax compliance as dependent variable and condition (EV information vs. control) as predictor was run. A random intercept for participants was included to account for the 24 repeated decisions. Presence of EV information did not reach significance as a predictor for tax compliance (*OR* = 0.77, 95% CI [0.52 – 1.13], p = .186).

Hypothesis 2 took a closer look at the kind of EV information that was given, assuming that the most prominent and clearest indicator of EV, the visual cue, would lead to the smallest number of tax compliant decisions, followed by the numerical cue and then the verbal explanation. To test hypothesis 2 a logistic regression with tax compliance as dependent variable and condition (control vs. verbal EV information vs. numerical EV cue vs. visual EV cue) was conducted. Again, a random intercept for the 24 repeated decisions was included. The analysis revealed that the expected order was not present in the data. Only the visual cue condition predicted tax compliance significantly (*OR* = 0.45, 95% CI [0.28 – 0.71], p = .001), but the other conditions did not reach significance. See Table 1 for Models 1 and 2.

Calculating the contrasts confirmed that there was a significant difference in tax compliance between control and visual EV cue condition of 0.806 (*SD* = 0.237, p = .004), between verbal explanation and visual EV cue condition of 0.733 (*SD* = 0.249, p = .017) and numeric EV cue and visual EV cue condition of 0.917 (*SD* = 0.242, p = .001). See Appendix B for the full table.

Table 1

EV information as predictor of tax compliance

	Model 1			Model 2		
	Tax compliance			Tax compliance		
	OR	*CI*	*p*	*OR*	*CI*	*p*
Intercept	1.61	1.16 – 1.24	.005	1.60	1.16 – 1.21	.004
EV information	0.77	0.52 – 1.13	.186			
Condition EV verbal				0.93	0.58 – 1.50	.765
Condition EV numeric				1.12	0.70 – 1.77	.639
Condition EV visual				0.45	0.28 – 0.71	.001

Note. N = 4128. Random intercept for N = 345 individuals.

An exploratory look at risk attitudes revealed that participants were moderately risk seeking, scoring an average of 6.21 (SD = 2.12) points on the Holt and Laury (2002) risk aversion task and rating themselves an average of 5.66 (SD = 1.92) on the risk attitude item. To check robustness of the model results, the models were run again including the risk measurements. Both the Holt and Laury risk aversion and the self-rated risk attitude directly predicted tax compliance. A higher risk aversion score in the Holt and Laury task led to more tax compliance (B = 0.16, p <.001) and higher self-reported tendency to take risks led to lower tax compliance (B = -0.14, p = .003). As risk attitude did not interact with experimental conditions, results of hypotheses 1 and 2 are unaffected. Further, the results were robust against manipulation and attention checks, as including them in the model revealed no influence. There were no interactions between gender and experimental conditions or age and experimental conditions. See Appendix B for the complete tables.

Another exploratory look was taken on the interactions between tax parameter and condition. There were significant positive main effects of 20% audit probability (OR = 4,47, 95% CI [3.39 – 5.88], p < .001) and 30% audit probability (OR = 37.47, 95% CI [26.63 – 52.74], p<.001) and fine level (OR = 1.99, 95% CI [1.64, 2.42], p < .001), suggesting that these singular parameters act in the predicted way. As for interaction effects, there was a significant interaction between tax rate and condition for the numerical cue condition (OR = 0.49, 95% CI [0.37 – 0.64], p < .001) and the visual cue condition (OR = 0.51, 95% CI [0.38 – 0.67] p <.001). In Figure 2 we can see that tax rate acted differently for the verbal explanation and control condition compared to the visual cue and numerical cue condition. Whereas higher tax rate showed an increasing slope for verbal explanation and control condition, the slope was decreasing for visual and numerical cue condition. A significant interaction was found between audit probability and condition for the numerical cue condition on audit probability levels 20% (*OR* = 1.96, 95% CI [1.29 – 2.97], *p* = .002) and 30% (*OR* = 1.87, 95% CI [1.12 – 3.13],*p* = .017). Find the table summarizing the results of the logistic regression models with interactions between condition (visual expected value cue vs. numerical expected value cue vs. verbal expected value information vs control) and tax parameters (income, tax rate, audit probability, fine rate) as predictor of tax compliance in Appendix B.

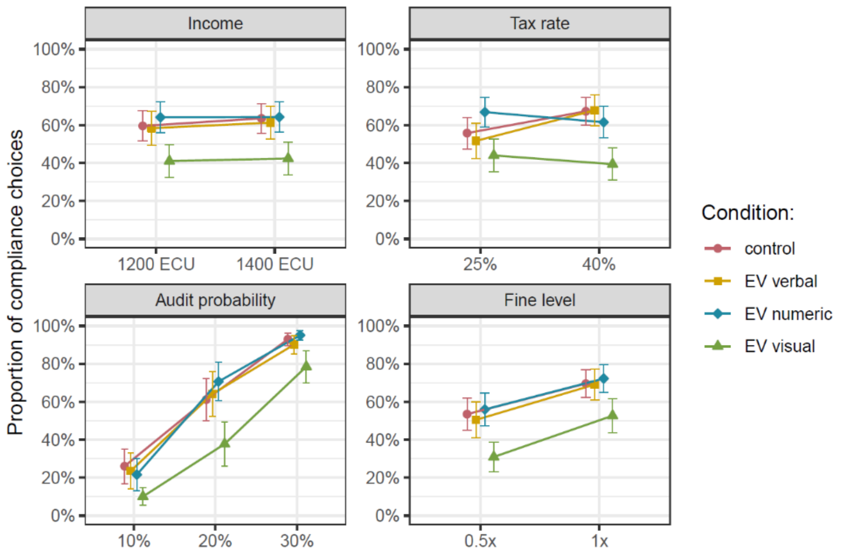

Figure 2. Interactions between experimental conditions (control vs. verbal EV information vs. numerical EV cue vs. visual EV cue) and tax parameters (income, tax rate, audit probability, fine level)

A further exploratory look at the expected rate of return from evasion was taken to interpret the finding that tax rate interacted with experimental condition in a way that tax compliance increased with higher tax rate in the control and verbal explanation condition but decreased in the numerical and visual cue condition. In fact, a higher tax rate is expected to decrease tax compliance in the A&S model as one underlying assumption is that of stable preferences. A higher tax rate increases the expected rate of return from evasion, i. e. the monetary benefit one gains when successfully evading tax. Figure 3 shows the proportion of compliance choices over the course of the 24 decision rounds per condition. The rounds are re-ordered according to their expected return from evasion, starting with the round with the lowest return on the left, increasing to the right. With increasing monetary benefit when evading tax, relative tax compliance should steadily decrease. Applying the rules of the A&S model, the proportion of compliance choices should therefore steadily decrease from left to right. This assumption is violated twice by an increase of compliance choices (non-overlapping 95%-CIs). First at the increase of return from evasion from 0.23 to 0.27 and a second time when return from evasion increases from 0.28 to 0.37 for all experimental conditions. The first increase happens when the tax rate increases up from the low 25% to the high 40% and the audit probability increases from the medium 20% to the high 30%. The proportion of tax compliance drops back down when tax rate and audit probability decrease to 25% and 10% respectively. The second increase is again marked by an increase of tax rate from 25% to 40% and an increase of audit probability from 10% to 30%. This suggests that participants did not integrate all the information to form a decision (in the form of the return from evasion) but rather focused on single indicators. A higher tax rate reflects in a higher fine, but also in higher return from evasion as there is a higher gain when evading the tax. The deterrence by fine seems to drive the decision.

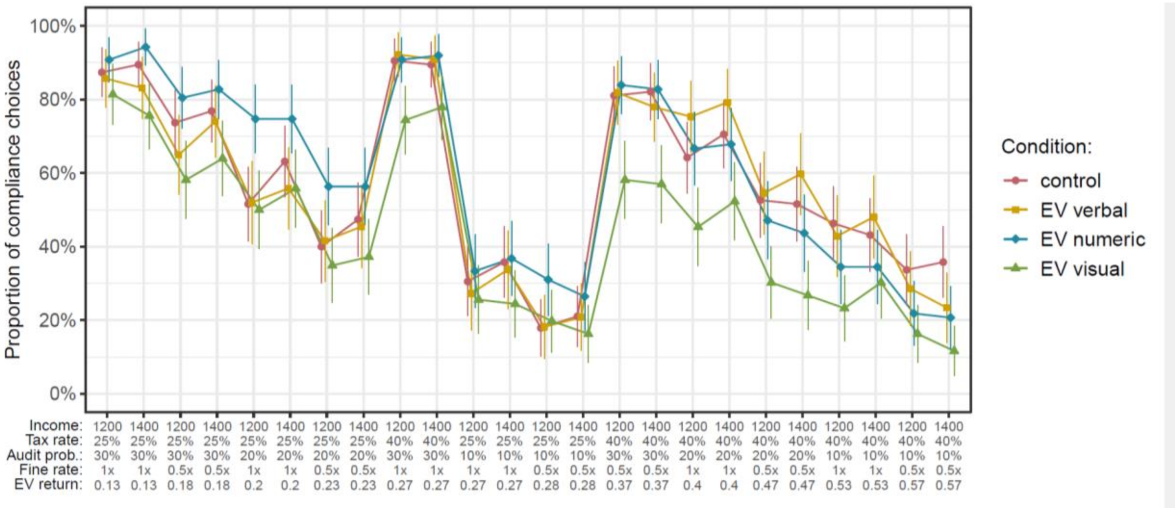

Figure 3. Proportion of compliance choices depending on the expected rate of return from evasion. The expected rate of return from evasion is ordered increasing from left to right.

Figure 4 reveals that both in the numerical (*OR* = 0.03, 95% CI [0.01, 0.10], *p* < .001). and the visual cue condition (*OR* = 0.05, 95% CI [0.02, 0.17], *p* < .001) the proportion of compliance choices decreases stronger with higher expected return from evasion than in the verbal explanation and the control condition. In contrast to the numerical cue condition, in the visual cue condition, compliance proportions were not different from the control condition when holding the expected return from evasion constant (*OR* = 1.05, 95% CI [0.45, 2.03], *p* = .882), however, compliance then significantly decreases with increasing expected return from evasion, ultimately tot the lowest compliance level. This decrease in rounds with higher expected rates of return drives the overall effect of condition (H2).

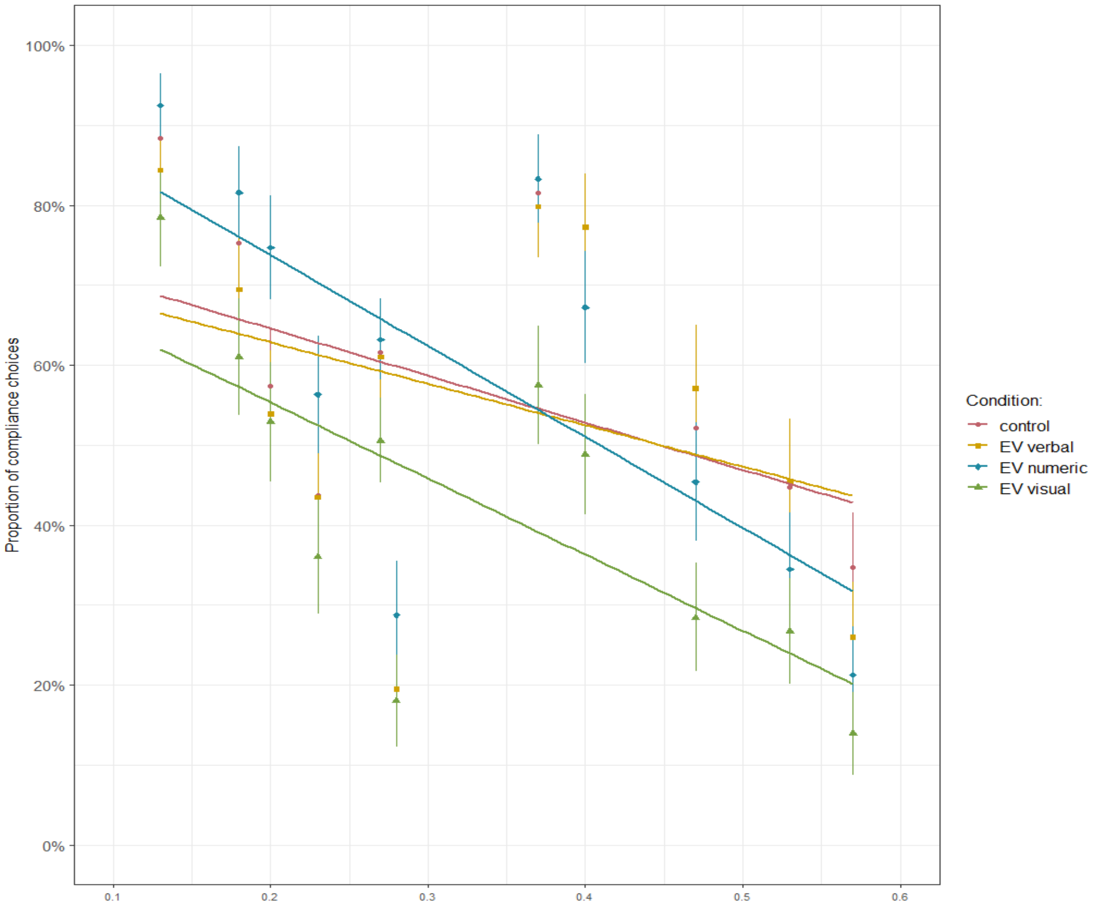

Figure 4. Linear trend of proportions of compliance choices depending on the expected rate of return from evasion. Expected rate of return from evasion is ordered increasing from left to right.

Process Hypotheses

Hypothesis 3a predicts more information acquisition and longer box opening times in the verbal EV information condition compared to the control condition. Two models were calculated to test this hypothesis. Model 3 was a regression with frequency of box openings as dependent variable and condition (control vs. verbal EV information) as predictor. Model 4 was a regression with total box opening time as dependent variable and condition (control vs. verbal EV information) as predictor. Both models did not reach significance (see Table 2).

Table 2

EV information as predictor of box opening frequency and time

	Model 3			Model 4		
	Frequency			Box opening time (log)		
	B	*CI*	*p*	*B*	*CI*	*p*
Intercept	7.47	6.92 – 8.02	<.001	8.32	8.12 – 8.52	<.001
Condition EV verbal	0.30	-0.52 – 1.12	.468	0.01	-0.29 – 0.31	.955

Note. N = 4128. Random intercept for N = 345 individuals. Frequency is the number of times a box was opened per round; Box opening time is the log transformed duration a box was opened in milliseconds per round.

Hypothesis 3b predicts more transitions between income and audit probability and fine and audit probability in the verbal EV information condition. Two models were calculated to test this hypothesis. Model 5 includes condition (control vs. verbal EV information) as a predictor of income-audit probability transitions and model 6 includes condition (control vs. verbal EV information) as a predictor of fine-audit probability transitions. Condition was not a significant predictor for either model (see Table 3).

Table 3

EV information as predictor of transitions (income-audit probability, fine- audit probability)

	Model 5			Model 6		
	Income-Audit probability transitions			Fine-Audit probability transitions		
	B	*CI*	*p*	*B*	*CI*	*p*
Intercept	0.46	0.38 – 0.54	<.001	1.72	1.53 – 1.92	<.001
Condition EV verbal	0.02	-0.09 – 0.14	.705	0.04	-0.25 – 0.34	.774

Note. N = 4128 observations. Random intercept for N = 345 individuals.

Hypothesis 4 concerns the ease of information processing. Lower decision times and a lower number of box openings indicate greater ease of processing. The visual EV cue was expected to generate the fastest decisions with the lowest number of box openings, followed by the numerical EV cue and the verbal EV information was expected to generate the longest decision times and the highest number of box openings. Two regression models with condition (verbal EV information vs. numeric EV cue vs. visual EV cue) as (1) predictor of frequency of box openings (total number of box openings relative to the number of boxes present) (Model 7) and (2) predictor of total box opening time (Model 8) were conducted. The visual EV cue did not yield fewer box openings or shorter decision time. The numeric EV cue did yield fewer box openings (B = -0.34, p = .001), but longer decision time (B = 0.37, p = .007) (see Table 4). The frequency of box openings relative to the number of boxes presented in the design can be seen in Figure 6 (6.2). The total frequency is lowest for the numerical EV condition. The total time spent (6.3) is, however, highest for the numerical EV condition. Participants in the numeric cue condition did open fewer boxes but took longer to finalize their decision.

Table 4

EV information as predictor of relative frequency of box openings and decision time

	Model 7			Model 8		
	Relative Frequency of box openings			Decision time (log)		
	B	*CI*	*p*	*B*	*CI*	*p*
Intercept	1.94	1.80 – 2.09	<.001	8.33	8.13 – 8.52	<.001
Condition EV numeric	-0.34	-0.54 – -0.14	.001	0.37	0.10 – 0.63	.007
Condition EV visual	-0.14	-0.34 – 0.06	.162	0.19	-0.08 – 0.45	.167

Note. N = 6000 observations. Random intercept for N = 345 individuals.

Hypothesis 5 expects a higher proportion of attention to explicit EV information compared to the four classic tax information boxes in the visual EV cue condition, as the visual cue is easier to process. This translates to more box openings of the visual cue box relative to the four classic tax information boxes and more time spent on the open visual cue box relative to four classic tax information boxes. Two regression models with condition (numeric EV cue vs. visual EV cue) as predictor of (1) the relative frequency of EV box openings and (2) relative time spent on EV boxes were conducted. The models showed significantly lower box openings of the EV cue box in the visual cue condition (B = -0.19, p

<.001) and significantly less time spent in the visual cue condition (*B* = -0.15, *p* <.001) (see Table 5). In Figure 5 we can see that both the relative frequency (6.2) and the relative time spent (6.4) the numerical cue condition has the lowest values in income, tax rate, audit probability and fine rate. In turn, this means there was more relative attention to the explicit EV information than in the visual cue condition. This contradicts the expectations.

Table 5

EV information as predictor of relative frequency of box openings and relative box opening time

	Model 9			Model 10		
	Relative Frequency of EV box openings			Relative time spent on EV boxes (log)		
	B	*CI*	*p*	*B*	*CI*	*p*
Intercept	0.38	0.36 – 0.41	<.001	0.36	0.33 – 0.39	<.001
Condition EV visual	-0.19	-0.23 – -0.16	<.001	-0.15	-0.19 – -0.10	<.001

Note. *N* = 4130 observations. Random intercept for *N* = 345 individuals.

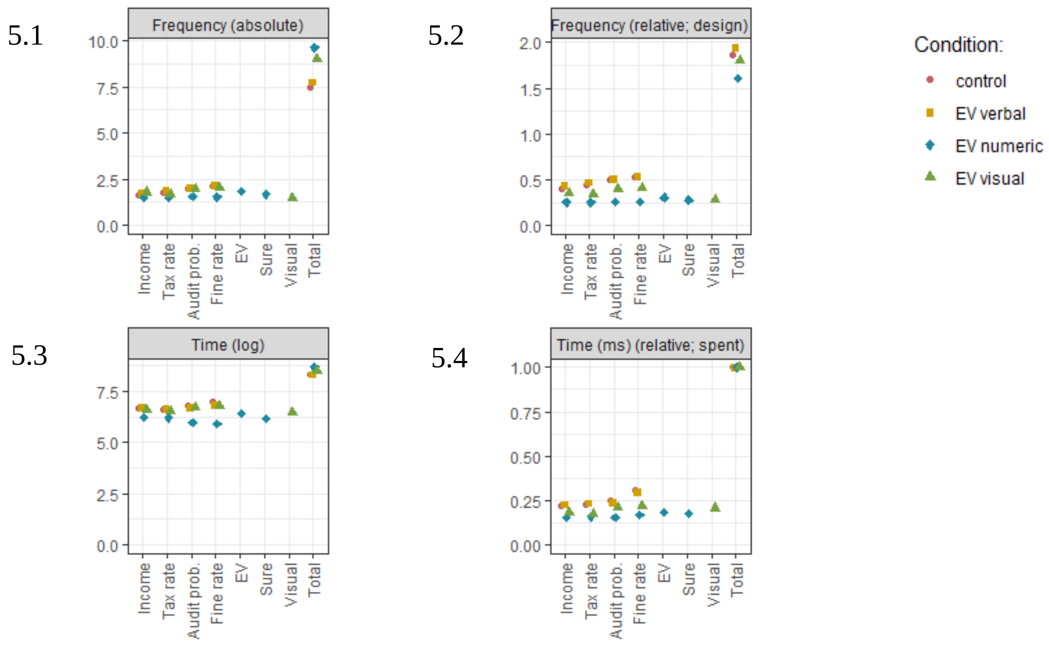

Figure 5. Frequency and duration of box openings. 5.1 shows the absolute frequency of box openings, 5.2 shows the frequency of box openings in relation to the total number of boxes, 5.3 shows the log-transformed duration of box openings and 5.4 shows the

Discussion

This study was designed to gain insights into tax behavior that go further than the outcome of decisions. Previous research has largely focused on decision outcomes to find answers to tax behavior, but contradicting findings have left the answers inconclusive. The need for a closer look at behaviors before finalizing the decision has been recognized in this study and process data were collected using MouselabWEB (Willemsen & Johnson, 2011). Compared to Kogler et al.'s (2020) study a greater variety of explanations and cues concerning the EV of evasion were used to gain insights into how information about this EV influences its use or lack thereof. The interest of this study was twofold. First, looking at the degree of tax compliance depending on the information about EV given, can resolve the question of how participants finally decided. Second, the process data give insights into how the information acquisition was influenced by the information about EV.

Looking at the outcome hypotheses, it was revealed, that only the visual cue had an influence on the tax compliance. The visual cue was very explicit, and even hinted how beneficial it was to evade, combining all the steps, including the comparison in one cue. It could mean that that a numerical cue, even though it takes out the calculation part of an EV-based decision, is still too ambiguous to understand. Given that the experiment included very detailed explanations of EV and how to use it and items to check whether participants had understood the concept, another explanation could be, that people are simply hesitant to decide based on EV. In any case,it takes a lot to shift people's behavior to that proposed by the A&S model.

The core of the EV of evasion is that all the parameters are combined into one number that takes every bit of information into account and makes it comparable to the sure outcome. It is then possible to compare the two courses that one can take, pay tax and receive the sure outcome or evade. Seeing that participants needed to be pushed heavily towards this integration of all parameters into one indicator a look at the influence of single parameters is of interest. Most striking is how tax rate acted in the different experimental groups. An increase in tax rate led to higher tax compliance in the control and the verbal explanation conditions, but lowered tax compliance in the numerical and visual cue conditions. To understand this interaction, one must first look at how tax rate influences the relation between sure outcome and EV of evasion. First, it must be highlighted that the rational choice is to evade tax whenever the EV exceeds the sure outcome. This relation is not influenced by the level of tax rate. When looking for the point of equity of sure outcome and EV of evasion we have

$$I - (t\ I) = p\ (I - f\ t\ I) + (1 - p)\ I$$

I being the Income, t the tax rate, p the audit probability and f the fine rate (amount by which the tax due is multiplied; Note that a fine rate of one would mean, that the tax due has to be paid back, but there is no actual fine on top. Any number larger than one would mean, there is a fine). Solving this equation reveals that the point of equity is only determined by the audit probability and the fine rate:

$$1 / p = f$$

Any fine rate larger than 1 / p would mean that it is more beneficial to evade tax as the EV of evasion is larger than the sure outcome and vice versa. Tax rate and income, however, leave this relation unaffected. How does tax rate influence the EV then? A higher tax rate results in a higher EV, or in other words creates a larger return from evasion. The amount a person can gain from evading tax gets bigger with a higher tax rate. A higher return from evasion should motivate to evade tax more than a lower return from evasion.

This expectation was not met in the data. Participants did not decide according to the expected rate of return from evasion. Ordering the tax decisions by return from evasion revealed that the proportion of compliance choices did not steadily decrease with increasing return from evasion. Rather there was an increase at two points. These points are marked by a high tax rate in combination with the highest audit probability used in this experiment. It has to be highlighted that tax rate both influences the tax due and the fine that has to be paid if an evasion is detected. With a higher tax rate, the tax due is elevated and with it the return from evasion which is a motivator for evasion. At the same time the fine is elevated, acting as a deterrence factor. One way to explain the increase in tax compliance can be found in Prospect Theory (Kahneman & Tversky, 1979). The loss, in this case the fine, is overweighted and looms larger than the gained tax due upon evasion. Participants may have focused more on the imminent fine and decided not to take the risk. What needs to be done in order to understand the full impact of the tax rate, is to integrate the audit probability in the calculation. Looking at the audit probability and the fine separately may have encouraged participants to overestimate the risks. Given that the 30% audit probability was the highest involved in this experiment, participants may have taken the other audit probabilities (10% and 20%) as an anchor (Tversky & Kahneman, 1974) and overestimated the impact of a 30% audit probability even more. Most important, however, is that participants seemed to have looked at the information separately instead of calculating EVs, as only the interaction of all parameters reveals the true benefits of either evading or paying tax. Only by performing these calculations, it is revealed that a 30% audit probability does not reduce the return from evasion, even at a 40% tax rate.

Looking back at the interaction of tax rate and experimental condition, it can be concluded, that providing participants with EV information that has integrated all parameters, reduces the bias. With the parameters chosen for this experiment, a higher tax rate creates a higher return from evasion. Providing a numerical or visual cue that combines all the information shifts the behavior more towards what is expected by the A&S model, tax evasion.

The conclusion that a strong indicator is needed to shift people’s behavior towards model conformity is supported by process data. If only an explanation was needed to motivate people to apply the EV to form decisions it should reflect in the pattern of information search. Participants did not look at information longer or more often when receiving an explanation of the EV beforehand. They did also not transition between income and audit probability or between fine and audit probability more often. This was even though they had received detailed and visually supported explanations of the EV. It was also made sure that participants understood the explanations they had been given with manipulation checks.

The question remains why they did not put the concept to use. Looking at research in gambling experiments (Li, 2003; Colbert et al., 2009), EV use is scarce, which matches the findings in this tax experiment. There are circumstances, under which EV use is stimulated in gamble experiments, but they are very specific: EV information is given in form of an explanation of the concept and the decision is embedded in a multiple-play context. To be more precise, the multiple-play context refers to playing the same gamble over and over again, such as 100 urn draws from an urn with the same distribution of red and yellow balls (Colbert et al., 2009). Looking at this tax experiment, the parameters change with every decision. It does therefore not fall in the multiple-play category. As Colbert et al. (2009) put it, the decision maker in the single-play context faces two outcomes, either win or lose, which are not reflected by the EV.

This experiment of course has one more characteristic: it is a lot more complicated than a gamble. Working out the EV takes more than just a simple multiplication. Four parameters all interact and have to be integrated in the calculation, which takes effort. People may not be motivated to perform all the calculations but rather rely on estimating the outcome based on single parameters. Taking the data of this experiment together, knowledge of the EV and how it is calculated does not appear to be enough to shift people's behavior towards making decisions in the way the A&S model predicts.

While giving an explanation of the EV and how to apply it to tax decisions was expected to enhance the information search, giving more information in form of explicit EV cues was expected to lessen it, as the information was already presented in a more compact way. Interestingly, this was not found. Participants opened fewer boxes in the numeric cue condition but took longer to decide. This hints at them processing the information deeper. One explanation could be that the numerical cue created curiosity in how these numbers relate to the parameters and made them think more about them. The numerical cue was, however, not enough to evoke more model conform decisions. This deeper processing did not aid the decision-making process towards rationality. Another explanation is that participants did not simply decide based on which number, sure outcome or EV of evasion, was bigger, but considered other factors. Giving a numerical cue triggered the thought about the EV. Fewer boxes were opened but the information was processed longer because participants did not trust the information enough to decide for evading the tax. As the EV of evasion was larger in every tax decision that was to be made in the experiment, evasion was the model conform choice in every round. Comparing the numbers does leave room for interpretation. If the sure outcome and the EV of evasion are closer together it may seem like it is not worth the risk. How far the sure outcome and the EV of evasion are apart, reflects in the expected return from evasion. In fact, a stronger influence of the return from evasion was observed in the numerical cue condition. This hints that participants did make use of the extra cue but considered their decision carefully. The cue did not increase tax evasion but made the rate of return more relevant.

Lastly it was found that participants paid less attention to the explicit EV cue in the visual cue condition than they did in the numerical cue condition in proportion to the four classic tax information boxes. It was expected that less attention to the classic information was needed as all the information was already included in the visual cue which makes information processing easier. Participants in the visual cue condition did decide more frequently to evade, which was indicated as the more beneficial choice. The attention to the classic tax information did not take away from that, the influence of the visual cue still overweighed, as no other condition showed a reduction of compliance choices. This attention to the classic tax information was unnecessary, as it could only affirm the visual cue. In the numerical cue condition, generally fewer boxes were opened, the decision time was longer and proportionally the attention was more focused on the explicit EV cue. This again addresses the last step in the decision, comparing the sure outcome to the EV of evasion. Apparently, this step needed more attention than it was expected. Rather than making the decision quick and easy, only having to find the larger number and deciding for the action attached to it, people start to think and weigh.

Conclusion

The results of this study point out that the A&S model does not reflect what actually happens during the decision process in tax decisions. This is not due to people not understanding the concept of an EV of evasion. Even with clear instructions and hints, people did not show less compliance. Only a very clear cue, that directly told participants what they should do, reduced tax compliance. People do not integrate bits of information into one indicator and decide based on comparison. Rather, it seems, the attention lies elsewhere. Single deterrence factors, i. e. the fine, play a role and weighing the rate of return. This points out that the focus of tax research should shift away from the classic model as people do not integrate information the way it proposes.

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Appendix A
Materials

This appendix features materials used in this study, including the risk measurements preceding the experiment, parameter explanations, pre and post experimental manipulation checks, and the motivational posture questions used. Study materials can also be viewed at https://osf.io/j8kn3/.

Risk measurements

Self reported risk attitude

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?
Please tick a box on the scale, where the value 1 means: ‘not at all willing to take risks’ and the value 10 means: ‘very willing to take risks’.

Holt and Laury risk aversion task (incentivized)

The first part of the study starts now. You will be presented with 10 lottery pairs. For each lottery pair, please choose either “Option A” or “Option B”.
You will make 10 decisions, however, only one of these decisions will be randomly selected to determine your payment at the end of the study.

Before you make your decisions, please look at the structure of the lottery pairs. For decision 1 (first row):
Option A pays 200 ECU with a probability of 10% and 160 ECU with a probability of 90%;
Option B pays 385 ECU with a probability of 10% and 10 ECU with a probability of 90%.

The following lottery pairs (row 2 - row 10) are similar with the exception of increasing probabilities for the higher payments the further down they are in the table. In row 10 the higher payment will be a sure outcome for both Options, so that your decision is between 200 ECU (Option A) and 385 ECU (Option B).

In conclusion, you will make 10 decisions: For each decision you will choose between Option A and Option B. You may choose Option A for some lottery pairs and Option B for others. Furthermore, you may change your decisions and make them in any order of your preference.

When you are finished, please click the “Next” button.

Lottery pairing	**Option A: Payoffs (in ECU) and their probabilities**				**Option B: Payoffs (in ECU) and their probabilities**	
1	Probability 10%	ECU 200	o A	o B	Probability 10%	ECU 385
	Probability 90%	ECU 160			Probability 90%	ECU 10
2	Probability 20%	ECU 200	o A	o B	Probability 20%	ECU 385
	Probability 80%	ECU 160			Probability 80%	ECU 10
3	Probability 30%	ECU 200	o A	o B	Probability 30%	ECU 385
	Probability 70%	ECU 160			Probability 70%	ECU 10
4	Probability 40%	ECU 200	o A	o B	Probability 40%	ECU 385
	Probability 60%	ECU 160			Probability 60%	ECU 10
5	Probability 50%	ECU 200	o A	o B	Probability 50%	ECU 385
	Probability 50%	ECU 160			Probability 50%	ECU 10
6	Probability 60%	ECU 200	o A	o B	Probability 60%	ECU 385
	Probability 40%	ECU 160			Probability 40%	ECU 10
7	Probability 70%	ECU 200	o A	o B	Probability 70%	ECU 385
	Probability 30%	ECU 160			Probability 30%	ECU 10
8	Probability 80%	ECU 200	o A	o B	Probability 80%	ECU 385
	Probability 20%	ECU 160			Probability 20%	ECU 10
9	Probability 90%	ECU 200	o A	o B	Probability 90%	ECU 385
	Probability 10%	ECU 160			Probability 10%	ECU 10
10	Probability 100%	ECU 200	o A	o B	Probability 100%	ECU 385
	Probability 0%	ECU 160			Probability 0%	ECU 10

Explanation of parameters

As the information matrices were varied in the different experimental conditions, the explanations were adjusted to the different designs. Some examples of the explanations are shown here.

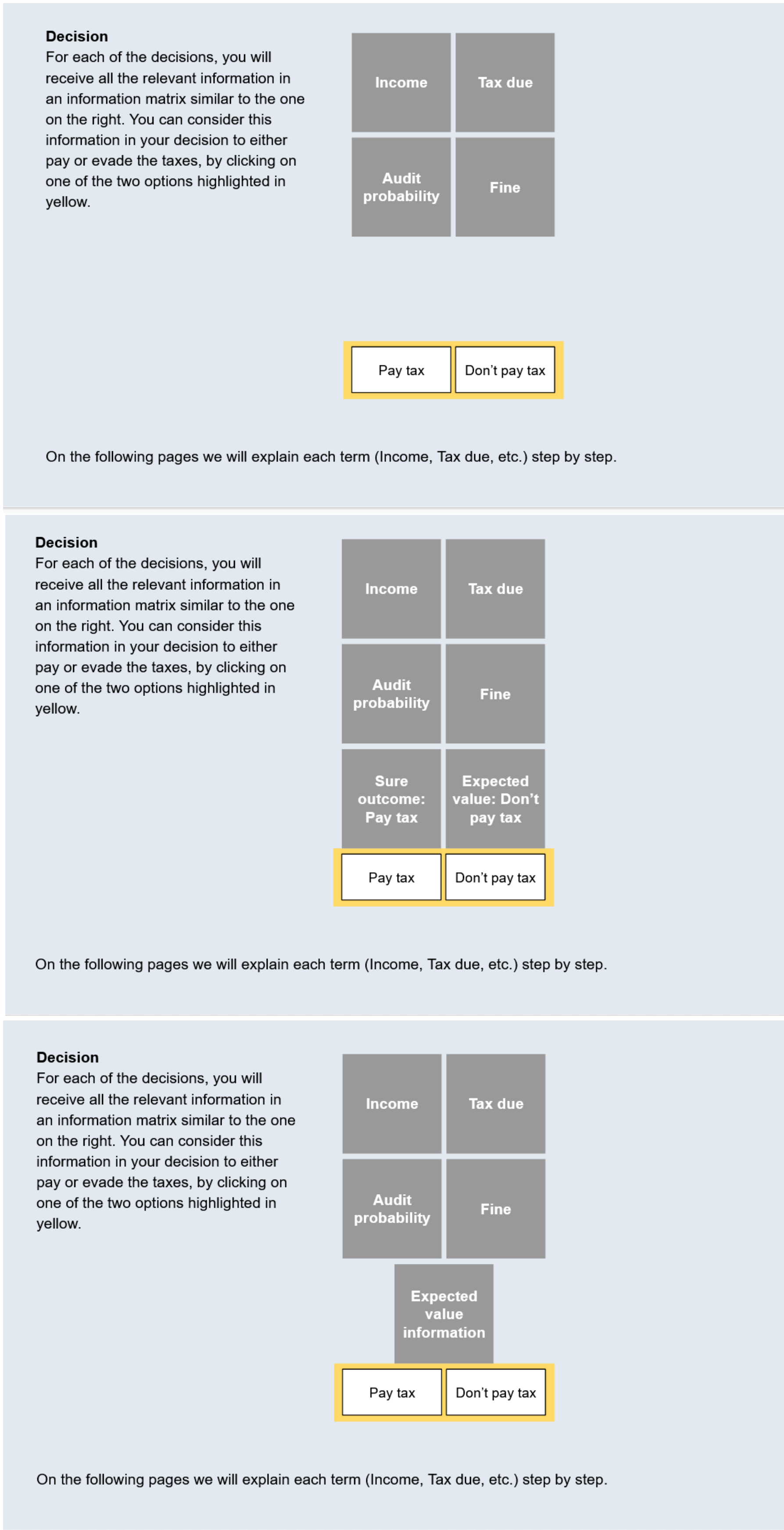

Figure A1. First page of parameter explanations in the different conditions. Control and verbal explanation condition are on the top, numerical cue condition in the middle and visual cue condition on the bottom.

Figure A2. Income explanation as featured in the control and verbal explanation condition.

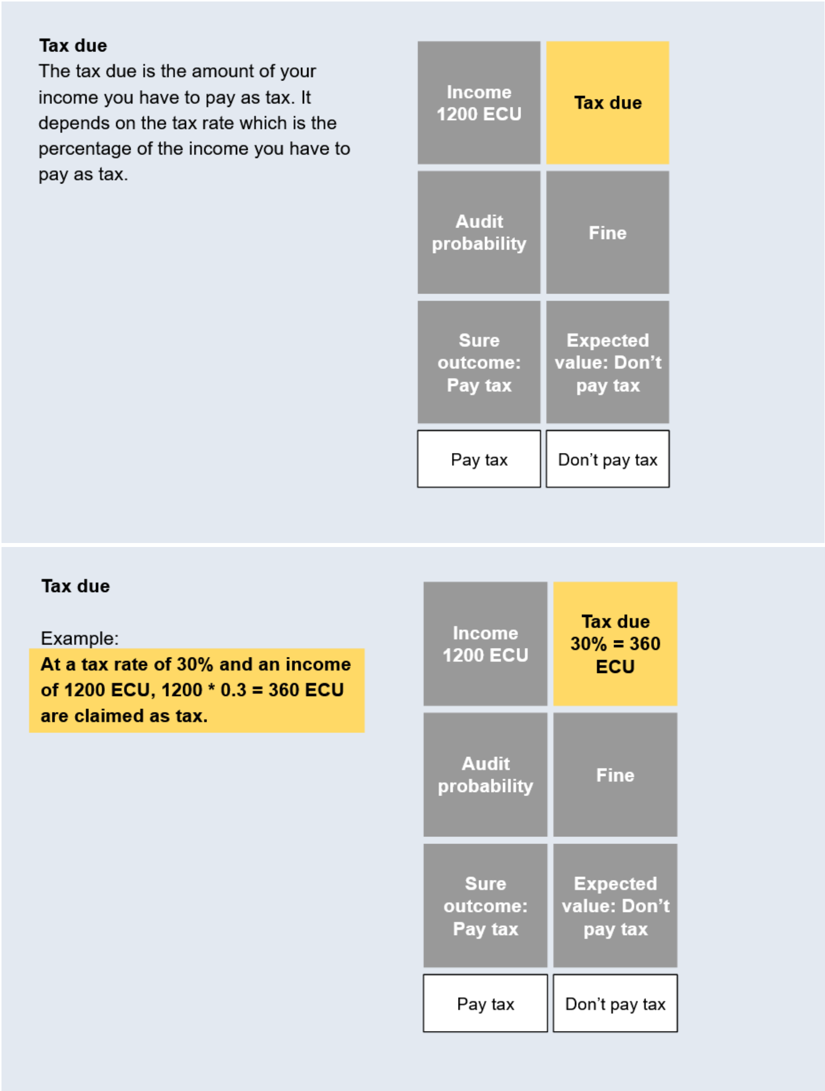

Figure A3. Tax due explanation as featured in the numerical cue condition.

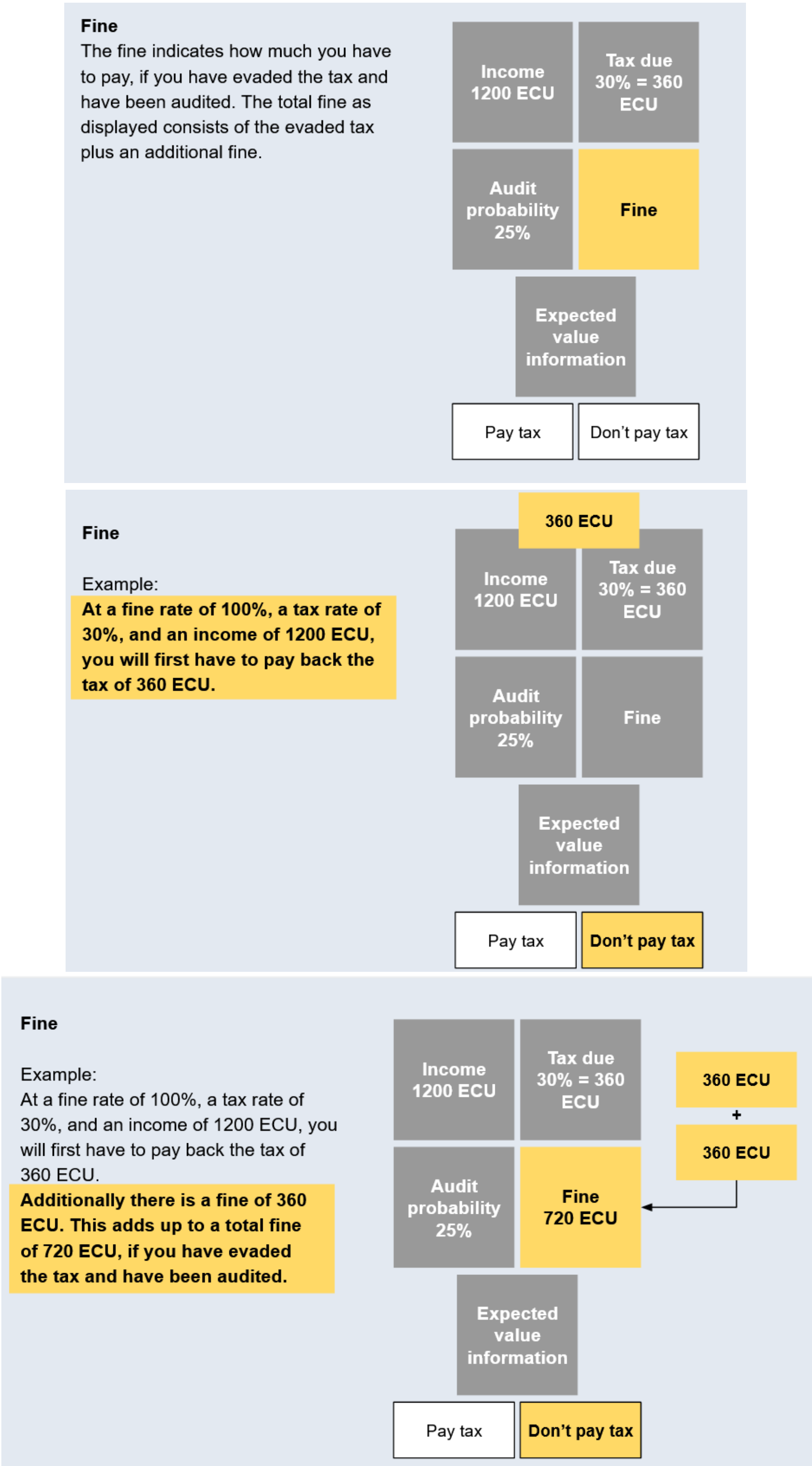

Figure A4. Fine explanation as featured in the visual cue condition.

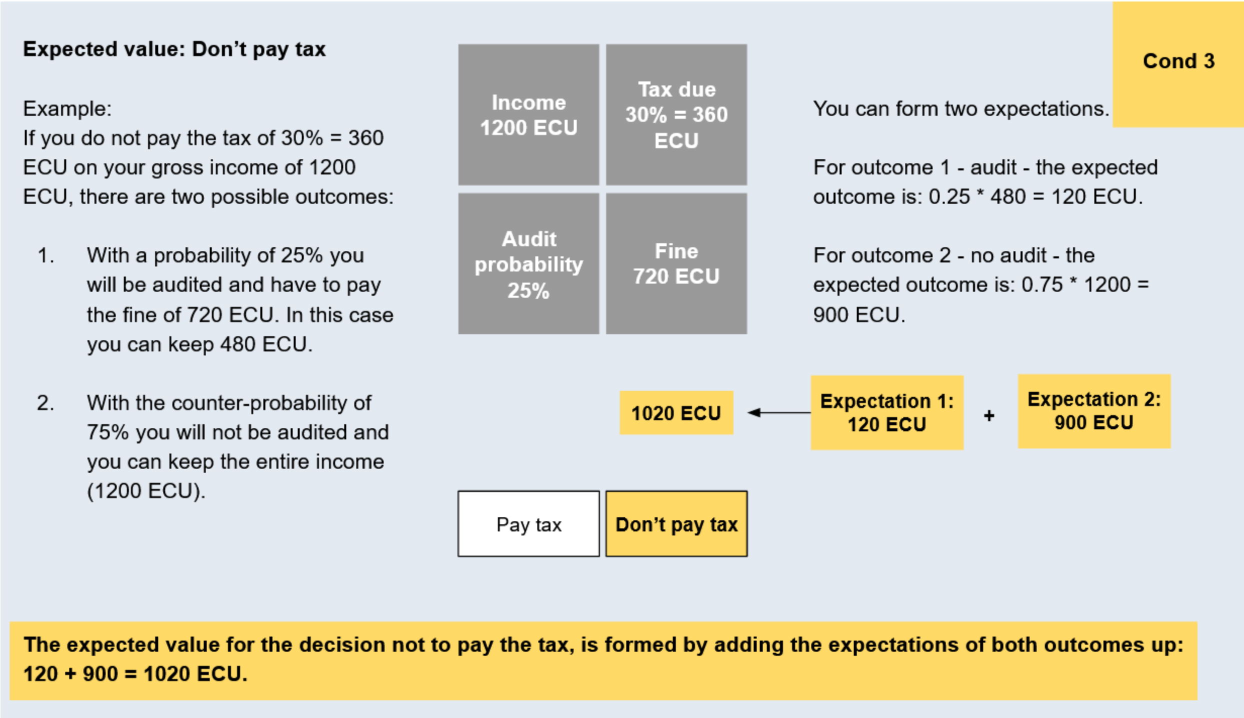

Figure A5. Expected value explanation as featured in the verbal explanation condition.
Note. This is the last page of the expected value explananation. Several pages with step by step explanations preceded this one. There was explanation of expected value in the control condition.

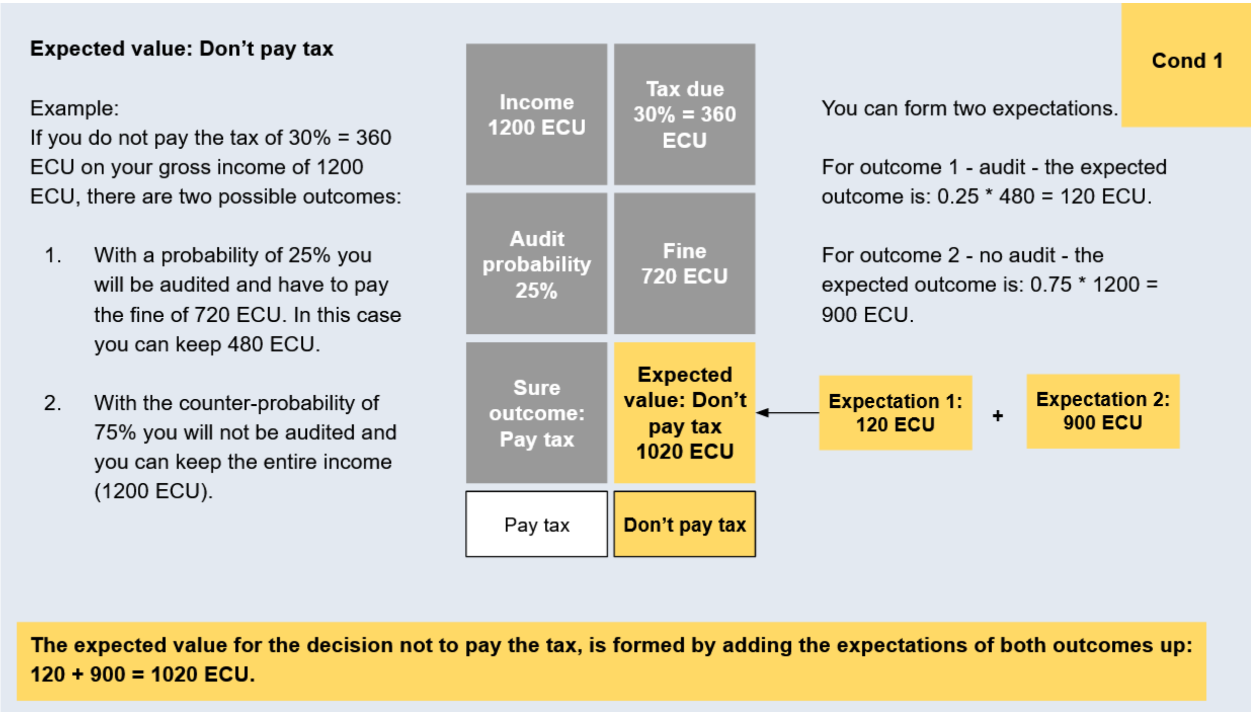

Figure A6. Expected value explanation as featured in the numerical cue condition.
Note. This is the last page of the expected value explanation. Several pages with step by step explanations preceded this one.

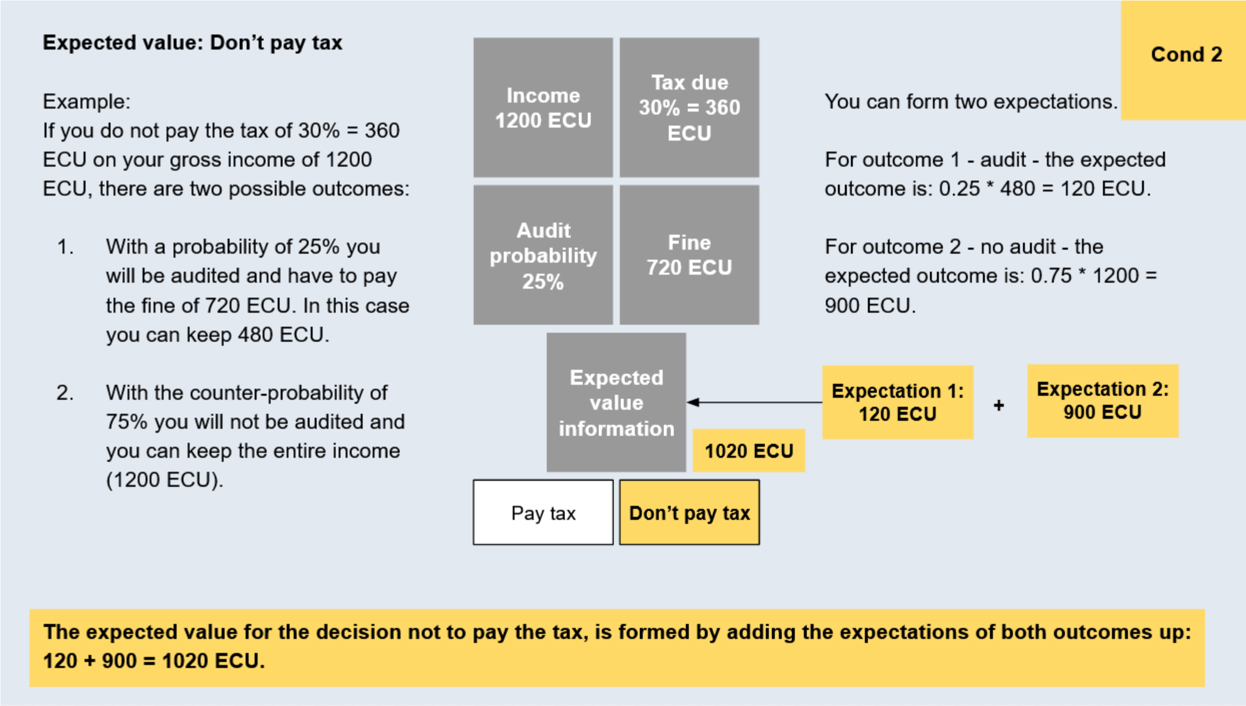

Figure A7. Expected value explanation as featured in the visual cue condition.
Note. This is the last page of the expected value explanation. Several pages with step by step explanations preceded this one.

Pre experimental Manipulation Check

Income 1000 ECU	Tax rate 300 (30%)
Audit probability 10%	Fine 600 ECU

Please solve the following tasks in relation to the example above to test your understanding of the instructions.
Please use only whole numbers to answer the questions.

1. How much would your remaining income be, if you choose "don't pay" and there is no audit?
2. How much would your remaining income be if you choose "pay"?
3. If you had to make this decision 10 times, how often could you expect to be audited?
4. How much would your remaining income be if you choose "do not pay" and you get audited?

Post experimental Manipulation Check

Think back to the instructions of the second part and indicate whether the following statements are true or not.
(1 = True, 0 = False, 2 = Do not know)

The safe outcome of the tax decision in the experiment indicates the remaining amount after paying the tax. (**true**, Cond1, 2, 3)

The audit probability indicates the chance of a tax inspection taking place in the respective round. (**true**)

The expected value of evasion represents the average outcome of choosing tax evasion. (**true**, Cond1, 2, 3)

If the tax rate is 50% on an income of 1000 ECU, the resulting tax is 300 ECU. (**false**)

The comparison of the safe outcome with the expected value of choosing evasion is helpful if a mathematically optimal decision is to be made. (**true**, Cond 1, 2, 3)

The expected value of choosing evasion describes exactly how much money you have left in the respective round when you do not pay the tax. (**false**, Cond 1, 2, 3)

The fine consists of paying back the unpaid tax plus an additional fine. (**true**)

If the safe outcome is lower than the expected value of choosing evasion, it pays off to pay the tax from a mathematical point of view. (**false**, Cond 1, 2, 3)

What were the tax rates over the repeated decisions in the second part of the study?
25% and 40% (**true**)
20% and 30%
10% and 20%

What were the audit probabilities over the repeated decisions in the second part of the study?
5%, 15%, and 25%
10%, 30%, and 50%
10%, 20%, and 30% (**true**)

Motivational Postures

Please indicate to what extent you agree with the following statements:
Note that these statements refer to the society you live in.
(1 = Fully disagree; 5 = Fully agree)

Commitment
Paying tax is the right thing to do.
Paying my tax ultimately advantages everyone.
I think of tax paying as helping the government do worthwhile things.

Game playing
I like to talk with friends about the gaps and loopholes in the tax system.
I enjoy exploring the gaps and barriers of tax law.
I find pleasure in finding a way to minimize my tax payments.

Appendix B

Contrasts and robustness checks

This appendix consists of models with risk aversion, manipulation checks, gender and age as moderator of tax compliance and the table of the contrast analysis.

Table B1

Holt and Laury (HL) risk aversion and risk item as predictors of tax compliance

	Compliance Model HL			Compliance Model HL*condition			Compliance Model Item			Compliance Model Item* condition		
	OR	*CI*	*p*	*OR*	*CI*	*p*	*OR*	*CI*	*p*	*OR*	*CI*	*p*
Intercept	0.48	0.29 – 0.81	.005	0.56	0.24 – 1.32	.185	2.88	1.69 – 4.90	<.001	5.04	1.97-12.90	<.001
HL	1.17	1.08-1.27	<.001	1.19	1.04-1.37	.012						
verbal				1.10	0.28-4.29	.890				0.68	0.16-2.80	.590
numeric				0.87	0.24 – 3.19	.830				0.69	0.17 – 2.84	.610
visual				0.38	0.09 – 1.53	.174				0.21	0.05 – 0.86	.031
Verbal*HL				0.95	0.77 – 1.18	.663						
Numeric*HL				1.03	0.84 – 1.27	.762						
Visual*HL				1.01	0.82 – 1.25	.937						

Item	0.87	0.80 – 0.95	.003	0.82	0.70 – 0.95	.011
Verbal*item				1.05	0.83 – 1.34	.662
Numeric*item				1.09	0.86 – 1.37	.482
Visual*item				1.14	0.90 – 1.46	.270

Note. *N* = 8040 observations for HL models and *N* =8280 observations for Item models. Random intercept for N = 345 individuals.

Table B2

Manipulation checks as predictors of tax compliance

	Compliance Model Check1*condition			Compliance Model Check2*condition		
	OR	*CI*	*p*	*OR*	*CI*	*p*
Intercept	2.10	0.30 – 14.69	.454	0.87	0.07 – 10.88	.911
verbal	1.55	0.11 – 21.18	.744	3.81	0.19 – 76.29	.382
numeric	5.20	0.31 – 86.38	.250	7.76	0.35 – 169.66	.193
visual	1.56	0.10 – 24.36	.752	2.85	0.14 – 58.48	.498
Check 1	0.73	0.08 – 6.90	.780			
Verbal*check1	0.53	0.02 – 11.53	.686			
Numeric*check1	0.16	0.01 – 4.26	.277			
Visual*check1	0.22	0.01 – 5.55	.360			
Check2				1.92	0.13 – 27.26	.631
Verbal*check2				0.17	0.01 – 5.41	.315
Numeric*check2				0.09	0.00 – 3.04	.181
Visual*check2				0.10	0.00 – 3.05	.185

Note. Check 1 was pre-experimental using an example of a tax decision. Check 2 was post-experimental using true or false statements. *N* = 8280 observations. Random intercept for *N* = 345 individuals.

Table B3

Gender as predictor of tax compliance

	Compliance Model Gender			Compliance Model Gender*condition		
	OR	*CI*	*p*	*OR*	*CI*	*p*
Intercept	1.58	1.23 – 2.02	<.001	1.87	1.18 – 2.94	.007
Gender [male]	0.72	0.51 – 1.02	.065	0.74	0.39 – 1.40	.354
verbal				1.01	0.50 – 2.08	.968
numeric				1.16	0.61 – 2.20	.644
visual				0.40	0.20 – 0.78	.007
verbal*gender				0.90	0.35 – 2.36	.835
numeric*gender				0.88	0.35 – 2.21	.787
Visual*gender				1.26	0.50 – 3.19	.619

Note. *N* = 8280 observations. Random intercept for *N* = 345 individuals.

Table B4

Age as predictor of tax compliance

	Compliance Model Age			Compliance Model Age*condition		
	OR	*CI*	*p*	*OR*	*CI*	*p*
Intercept	0.63	0.38 – 1.04	.069	0.45	0.16 – 1.31	.143
Age	1.02	1.01 – 1.03	.002	1.04	1.01 – 1.07	.014
verbal				1.95	0.44 – 8.70	.382
numeric				2.34	0.60 – 9.05	.218
visual				0.98	0.22 – 4.26	.976
verbal*age				0.98	0.94 – 1.02	.288
numeric*age				0.98	0.94 – 1.01	.226
visual*age				0.98	0.94 – 1.02	.300

Note. *N* = 8256 observations. Random intercept for *N* = 345 individuals.

Table B5

Contrast analysis of conditions

	Contrast estimate	*SD*	*P*
Control – EV verbal	0.072	0.243	0.991
Control – EV numeric	-0.111	0.236	0.966
Control – EV visual	0.806	0.237	0.004
EV verbal – EV numeric	-0.183	0.248	0.881
EV verbal – EV visual	0.733	0.249	0.017
EV numeric – EV visual	0.917	0.242	0.001

Note. Results are given on the log odds ratio scale.

Appendix C

Interaction effects between experimental condition and tax parameters

Table C1

Interaction effects between experimental condition and tax parameters

	Compliance Income*condition			Compliance Tax rate*condition			Compliance Audit probability*condition			Compliance Fine rate*condition		
	OR	*CI*	*p*	*OR*	*CI*	*p*	*OR*	*CI*	*p*	*OR*	*CI*	*p*
Intercept	1.47	1.05 – 2.06	.023	1.26	0.90 – 1.77	.176	0.35	0.22 – 0.57	<.001	1.15	0.82 – 1.62	.424
Condition EV verbal	0.95	0.58 – 1.57	.874	0.85	0.51 – 1.40	0.518	0.87	0.43 – 1.77	.706	0.88	0.53 – 1.47	.639
Condition EV numeric	1.21	0.75 – 1.96	.453	1.60	0.98 – 2.60	0.059	0.78	0.39 – 1.56	.485	1.10	0.67 – 1.81	.692
Condition EV visual	0.47	0.29 – 0.77	.002	0.62	0.38 – 1.02	0.058	0.32	0.16 – 0.64	<.001	0.39	0.24 – 0.64	<.001
Income	1.18	0.98 – 1.43	.084									
Verbal*income	0.95	0.72 – 1.26	.738									
Numeric*income	0.85	0.65 – 1.12	.244									

Visual* audit probability 20%	Numeric* audit probability 20%	Verbal* audit probability 20%	Audit probability 30%	Audit probability 20%	Visual*tax rate	Numeric*tax rate	Verbal*tax rate	Tax rate	Visual*income	
									0.89	*OR*
									0.68 – 1.18	*CI*
									.429	*p*
					0.51	0.49	1.21	1.63		*OR*
					0.38 – 0.67	0.37 – 0.64	0.91 – 1.61	1.34 – 1.98		*CI*
					<.001	<.001	.195	<.001		*p*
1.22	1.96	1.30	37.47	4.47						*OR*
0.79 – 1.87	1.29 – 2.97	0.86 – 1.96	26.63 – 52.74	3.39 – 5.88						*CI*
.366	.002	.206	<.001	<.001						*p*
										OR
										CI
										p

Visual*fine rate	Numeric* fine rate	Verbal*fine rate	Fine rate	Visual* audit probability 30%	Numeric* audit probability 30%	Verbal* audit probability 30%	
							OR
							CI
							p
							OR
							CI
							p
				0.87	1.87	0.79	*OR*
				0.53 – 1.43	1.12 – 3.13	0.49 – 1.30	*CI*
				.594	.017	.357	*p*
1.25	1.03	1.10	1.99				*OR*
0.94 – 1.67	0.78 – 1.36	0.83 – 1.47	1.64 – 2.42				*CI*
.129	.841	.501	<.001				*p*

Note. N = 8280 observations. Random intercept for N = 345 individuals.

Appendix D

English and German Abstract

English Abstract

In tax compliance research, the Allingham and Sandmo model of income tax evasion has enjoyed great popularity. If decision makers comply to the model, they should decide to evade taxes whenever the expected profit of evasion exceeds that of honest tax paying. This means that decision makers should at least integrate all the tax information into one indicator, the expected value (EV) of evasion, to make a decision, which should both reflect in the decision outcomes and the decision process. A MouselabWEB experiment with 24 decision rounds with varying tax parameters (income, tax rate, audit probability, and fine rate) was conducted. EV information was varied between subjects (visual cue vs. numerical cue vs. verbal explanation vs. control). Only the clearest EV cue, the visual cue, evoked more model conform decisions. Ordering the decision rounds by their expected return from evasion, showed that evasion did not strictly increase with higher return from evasion. Giving a verbal explanation of EV did not evoke more model conform information acquisition behavior and process data indicated no clear order of conditions regarding the ease of information processing. All in all, results suggest that information is not readily integrated into an EV, but rather other factors, such as singular deterrence factors impact the decision unless there are clear visual instructions of EV use.

German Abstract

Das Allingham und Sandmo-Modell der Einkommenssteuer-Hinterziehung erfreut sich großer Popularität in der Steuerehrlichkeitsforschung. Modellkonformes Verhalten zeichnet sich dadurch aus, dass Steuern immer dann hinterzogen werden, wenn der erwartete Gewinn durch Hinterziehung größer ist als der der ehrlichen Steuerzahlung. Daraus lässt sich ableiten, dass Entscheider die gesamte Steuerinformation in einen Wert, den Erwartungswert der Hinterziehung, integrieren sollten um eine Entscheidung zu treffen. Dies lässt sich anhand von Entscheidungsergebnis und Entscheidungsprozess überprüfen. In dieser Arbeit wurde ein MouselabWEB-Experiment mit in 24 Entscheidungsrunden variierten Steuerparametern (Einkommen, Steuersatz, Überprüfungswahrscheinlichkeit und Strafsatz) durchgeführt. Die Information über den Erwartungswert wurde in einem Between-subjects-Design variiert (visueller Hinweis vs. numerischer Hinweis vs. verbale Erklärung vs. Kontrollbedingung). Nur der deutlichste Hinweis, der visuelle Hinweis, führte zu mehr modellkonformen Entscheidungen. Geordnet nach steigendem erwarteten Ertrag bei Hinterziehung zeigte sich, dass der Anteil der Hinterziehung nicht streng mit dem erwarteten Ertrag der Entscheidungsrunde wuchs. Prozessdaten zeigten bei einer verbalen Erklärung des Erwartungswerts nicht mehr modellkonformes Informationssuchverhalten. Weiters zeigte sich keine klare Ordnung der Leichtigkeit der Informationsverarbeitung. Zusammenfassend gibt die Datenlage des Experiments Hinweise darauf, dass erst deutliche Anweisungen, wie ein visueller Hinweis, dazu führen, dass die Information in einem Indikator gebündelt wird. Andernfalls zeigen einzelne Parameter unabhängig von anderen Parametern abschreckende Wirkung.