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Abstract

The evidence shows source-dependent entitlement to income sources and individuals are *reluctant to part with income they feel more entitled to*, e.g., earned labor income. Taxpayers may also be more reluctant to part with tax payments (evade more) from income sources they feel more entitled to- a form of mental accounting. We embed two main hypotheses within a rigorous theoretical model based on prospect theory. From incomes sources they feel more entitled to, taxpayers experience (i) greater loss aversion from paying taxes, and (ii) lower moral costs of evasion. We confirm the predictions of our model through MTurk experiments. Evasion is increasing in the tax rate and decreasing in the audit penalty. Moral costs influence taxpayers' decisions. Loss aversion, measured "directly" for the first time for each individual in an evasion experiment, reduces evasion, as predicted by our theory. Loss aversion, risk aversion, and their interaction, are critical determinants of evasion.

JEL-Codes: C910, C920, D820, D910, G210.

Keywords: mental accounting, tax evasion, loss aversion, morality, prospect theory, risk-aversion.

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1 Introduction

Mental accounting is one of the most promising areas in behavioral economics with a potentially rich domain of applications. Evidence suggests that (i) individual behavior is dependent on the source of income, and (ii) incomes and expenditures are not fungible across different mental accounts (Kahneman and Tversky, 1984; Thaler, 1985, 1999; Dhami, 2020, Vol. 5, Ch. 2). Thaler (1999, p. 186) gave a general definition of mental accounting: "*I wish to use the term 'mental accounting' to describe the entire process of coding, categorizing, and evaluating events.*" Yet, the implications of mental accounting are insufficiently explored, particularly in public economics.[1]

We consider the relation between mental accounting and tax evasion using a rigorous theoretical model, which is then subject to stringent empirical testing. We pose two direct questions. (1) Do people evade different amounts of tax when the source of their taxable income differs but for all other purposes, e.g., in their tax treatment, they are identical?[2] We compare labor income, *earned* in an experimental task, relative to non-labor income which is *unearned* during the experiment, e.g., bequest, gifts, lottery win, unexpected capital gains. (2) If, ceteris-paribus, evasion depends on the source of income, what is the explanation? Source dependent tax evasion behavior indicates mental accounting because potential tax evaders appear to code and categorize the two different kinds of incomes differently, although they are identical in all other respects, including their tax treatment.

Henceforth, we shall refer to *earned labor income* and *unearned non-labor income*, simply as *labor income* and *non-labor income*. Our proposed theory allows for any difference in the income sources provided the individual feels more entitled to one income source over the other. In our theoretical model, we use prospect theory for our tax evasion analysis (Wakker, 2010; Dhami, 2019, Vol. 1). This has several advantages over the alternative theories in the domain of tax evasion.[3]

1.1 Entitlements and mental accounting

Individuals feel different levels of *entitlements* from earned and unearned incomes (Hoffman and Spitzer, 1982; Cherry et al., 2002; List and Cherry, 2000; Parrett, 2006). In dictator game experiments, when income is earned, dictators reduce the amount transferred (Cherry et al.,

[1]The interested reader can follow up the references and the applications in Dhami (2020, Vol. 5, Ch. 2). These applications include: preferences over payment segregation and payment aggregation; implictions for the life cycle model in macroeconomics; payment of mortgages for consumer durables but pre-payment for vacations (the *red and black* of mental accounting); and the explanation of choice bracketing, self-control problems, coherent arbitrariness, house money effect, diversification heuristic, sunk costs, goals, and the patterns of retirement savings.

[2]In the real world, the tax treatment of different sources of incomes may differ. One great merit of experiments is the ability to control for this potential confound, which enables a cleaner test of the theory.

[3]Expected utility theory is inconsistent with the qualitative and quantitative data from tax evasion, and non-expected utility theories such as *rank dependent theory* and *prospect theory* provide a superior explanation of the stylized facts (Bernasconi, 1998; Yaniv, 1999; Bernasconi and Zanardi, 2004; Dhami and al-Nowaihi, 2007, 2010; Eide et al., 2011). In particular, expected utility provides quantitative predictions that are in error by a factor of up to a 100 and qualitative predictions (e.g., declared income that increases in the tax rate– *Yitzhaki puzzle*) that are inconsistent with the evidence; the explanation of these issues is unproblematic under prospect theory (Dhami and al-Nowaihi, 2007, 2010).

2002; Cappelen et al., 2007; Levitt and List, 2007); and when income of the receivers is earned, dictators increase the amount transferred (Oxoby and Spraggon, 2008). In ultimatum games, if the income of the proposer is earned, the responder's rejection rate falls (Lee and Shahriar, 2017). Dhami et al. (2020) find that in the presence of taxation and redistribution of income to respondents in an ultimatum game, earned income, relative to unearned income, reduces the (i) amount transferred to responders, and (ii) the minimum acceptable offer of the responders.

1.2 Transmission channels from entitlements to tax evasion

Our main hypothesis is that, ceteris-paribus, people are relatively less willing to part with earned labor income when they pay taxes, due to a greater sense of entitlement. We conjecture two channels through which this effect arises.

1. *Higher loss aversion from earned labor income*: Loss aversion has been found to be a key determinant of tax evasion (Dhami and al-Nowaihi, 2007, 2010; Engström et al., 2015; Rees-Jones, 2018) and much human behavior.[4] Furthermore, existing explanations of several mental accounting phenomena rely on loss aversion.[5] If loss aversion is relatively greater from earned income, then individuals are less willing to part with it, in the form of fines, in the state of the world where they are caught evading taxes. Hence, they will *evade less earned income*. We adapt the *bisection procedure* in Abdellaoui (2000) to elicit loss aversion and risk aversion "directly" from lottery choices, for each individual. Our data strongly confirms our conjecture. As far as we are aware, this is the first instance where subject-level loss aversion data is obtained and tied to tax evasion.[6]

2. *Lower moral cost from evading earned labor income*: Moral virtues are important and individuals are typically not willing to lie maximally, even when there is no chance of being caught, although partial lying is often observed (Dhami, 2019, Vol. 2, Section 3.2, 5.6). Moral virtues impose a variety of moral costs from engaging in illegal activity.[7] Hence, we assume that evasion imposes moral costs on a tax evader. Our second conjecture is that there are relatively lower moral costs of evading taxes on earned income to which one

[4]The assertion that loss aversion is one of the most important human preference parameters is well supported by the evidence and it is reinforced from the evidence on animal studies and from neuroeconomic studies (Dhami, 2019, Vol. 1; Dhami, 2020, Vol. 7).

[5]This includes the role of goals, effectiveness of defaults, the house money effect, and the segregation/combination of gains and losses (Soman and Cheema, 2004; Locke and Latham, 1990; Thaler and Johnson, 1990; Thaler 1985). Arguably, loss aversion is also implicated in the explanation of the red and black of mental accounting (Prelec and Loewenstein, 1998) and in the explanation of a mental account for daily incomes that accounts for the backward bending labour supply curve of labour (Fehr and Göette, 2007; Crawford and Meng, 2011).

[6]To be sure, the "indirect" implications/measurements of reference dependence and loss aversion for tax evasion have been studied before (Dhami and al-Nowaihi, 2007, 2010; Engström et al., 2015; Rees-Jones, 2018). However, in these cases loss aversion is inferred from observed behavior (e.g., bunching behavior of taxpayers). It is not directly measured for each individual from lottery choice tasks, which is what we do.

[7]Individuals might also wish to signal to themselves and to others that they possess moral virtues that are diluted with tax evasion (Bénabou and Tirole, 2002, 2003). The act of evading taxes might also induce guilt (Battigalli and Dufwenberg, 2007) or shame (Bicchieri, 2006; Elster, 2012). For a survey of several kinds of moral costs in the context of tax evasion, but within an expected utility formulation, see Andreoni et al. (1998), Slemrod and Yitzhaki (2002), Slemrod (2018), and Alm (2019). For the interaction between morality and tax evasion within an expected utility formulation, see in particular Gordon (1989), Erard and Feinstein (1994), and Alm and Torgler (2012).

feels more entitled. Thus, taxpayers will *evade more earned income*. We lack a method of directly measuring moral costs for each source of income but we provide strong indirect evidence for moral costs in our data.[8]

Note from 1 and 2 above, that the two channels (loss aversion and moral costs) work in opposite directions.[9]

1.3 Experiments, predictions, and findings

We have two treatments in a between-subjects design in an online experiment conducted on MTurk in June 2020. In the first treatment (T1) taxpayers only have earned labor income through solving a set of timed and tedious experimental tasks. In the second treatment (T2) taxpayers have only non-labor, experimenter-provided, income. Moving from T1 (labor income) to T2 (non-labor income): (i) *Loss aversion* falls, which increases evasion. (ii) *Moral costs* of evasion increase, which reduces evasion. Hence, the net effect is an empirical question. In addition, we explore the effects of the detection and enforcement parameters on the tax evaded. We control for taxpayer-specific preference characteristics (e.g., loss aversion, risk attitudes), economic characteristics (e.g., income, education, job), and demographic characteristics (e.g., age, gender, marital status). We consider exogenous variation in several policy parameters (e.g., tax rate, penalty rate, audit probability).

Our model predicts that tax evasion is decreasing in the deterrence parameters, audit probability and penalty rate, as in models based on expected utility theory (Allingham and Sandmo, 1972) and we confirm this with our data. However, under reasonable assumptions an expected utility analysis predicts that an increase in the tax rate reduces tax evasion (Yitzhaki (1974) puzzle), which is not empirically supported.[10] The Yitzhaki puzzle can be explained using prospect theory (Dhami and al-Nowaihi, 2007); we extend this theoretical result to mental accounting and we confirm it with our data. The empirical results support the predictions of our theoretical model. The estimated median loss aversion across all subjects is 1.73, which is comparable to findings in the literature (Chapman et al., 2019; Dhami, 2019, Vol. 1). Even when there is a negative penalty from tax evasion (i.e., an effective 100% subsidy to evasion), we find that taxpayers declare, on average, 31% of their income, which is consistent with the presence of moral costs of evasion.

Loss averse taxpayers are significantly less likely to evade taxes as compared to loss tolerant taxpayers. The probability of evasion is relatively lower in Treatment 1 (labour income). Since loss aversion and moral costs of evasion work in opposite directions (see above), the overall negative treatment effect, albeit only weakly significant at 10% level, indicates that loss aversion is a relatively stronger influence on evasion as compared to moral costs. As noted above, we do

[8]Future developments in neuroeconomics might open the way for direct measurements of morality costs (Yoder and Decety, 2018).

[9]We could invoke only the first channel and justify our data, but given the evidence on moral costs in illegal activity, it would not seem appropriate to do so.

[10]See, for example, Friedland et al. (1978), Clotfelter (1983), Andreoni et al. (1998) and Pudney et al. (2000). For a contrary result, see Feinstein (1991). For surveys, see Andreoni et al. (1998), Slemrod and Yitzhaki (2002), Slemrod (2018), and Alm (2019).

not directly measure differences in moral costs in the two treatments, hence, while our results are consistent with the second conjecture that we make in Section 1.2, we do not provide direct evidence for the conjecture.[11]

Taxpayers who are not single, and more educated taxpayers, are likely to evade less tax. The interaction of risk aversion with the treatment dummy is significant at the 1% level, as are the following two interaction terms between (i) loss aversion and the treatment dummy, and (i) loss aversion, risk aversion, and the treatment dummy. This enables us to identify significant intercept and slope effects in the explanation of tax evasion, as we vary loss aversion, risk aversion, and the treatment dummy. Indeed, we show that a joint consideration of loss aversion and risk aversion, which is a novel feature of our design, is essential to understanding tax evasion behavior. For instance, loss averse individuals, who are risk averse, and in Treatment 1, actually evade significantly lower tax, as compared to a variation in any of counterfactuals (loss tolerant, risk loving, Treatment 2). None of these results have an obvious explanation in the absence of mental accounting.

1.4 Relation to the literature

There is a small literature on mental accounting and tax evasion. Chambers and Spencer (2008) find that yearly tax refunds and monthly tax refunds are coded into different mental accounts. Jackson et al. (2005) report that taxpayers expecting a refund code third party agent fees in a different mental account that elicits a higher willingness to pay the agents. Muehlbacher and Kirchler (2013) find that small businesses keep a separate mental account for the end of the year tax to be paid to the government. Such taxpayers are more likely to comply with tax payments (Muehlbacher et al., 2017; Olsen et al., 2019). Fochman and Wolf (2015) find that taxpayers exhibit a difference in the mental accounting of gains (which applies to income) and losses (which applies to expenditure). Rees-Jones (2018) takes before-tax income as a reference point and exploits the kink at the reference point in prospect theory, to show that this predisposes taxpayers to evade more in the neighborhood of the kink. He estimates a \$34 impact of tax payments arising from the kink at the reference point but does not directly measure individual loss aversion.

1.5 Schematic outline of paper

Section 2 presents our model. Section 3 sets up the optimization problem, and provides the comparative static predictions. Section 4 outlines our theoretical approach to measuring loss aversion and risk attitudes. Section 5 describes the experimental design. Section 6 provides the descriptive statistics for the model and the findings on loss aversion and risk attitudes. Section 7 tests our comparative static predictions of the amount evaded with respect to the

[11] One might wonder if the moral costs in our paper are simply capturing some social norm of greater evasion of unearned income (Alm, 2019). We note that none of the preconditions for a social norm are present in our paper; these include, empirical expectations, normative expectations, and punishment of norm violators (Dhami, 2019, Vol. 2, Section 5.7). Thus, no social norms can be inferred from the behavior of our taxpayer. However, no definitive answer can be given to the question of whether subjects unknowingly used outside-the-lab social norms in their responses in our experiment. It is possible that moral costs capture some underlying personal moral norms. We are grateful to James Alm for raising this point.

audit penalty rate and the tax rate. Section 8 gives a multinomial probit analysis of the evaded tax and discusses its determinants. Section 9 concludes. Section 10 contains the Appendix, which collects all the proofs in the paper. The detailed instructions for the experiment are given in the Appendix of the working paper version, Dhami and Hajimoladarvish (2020).

2 The Model

In this section we describe our model of tax evasion.[12]

2.1 Basic setup

Suppose that there is a set $M = \{1, 2, ..., m\}$ of identical taxpayers and a typical taxpayer is indexed by i. Taxpayer i has taxable income given by W_{ij}, where the subscript $j = L, N$ denotes the source of income, i.e., either *labor income* (earned by solving tasks in an experiment) or *non-labor income* (experimenter-provided income). Our theory does not rest on this particular setup; all that we require is for the entitlements from the two income sources to be different.

Each source of income is taxed at the identical constant marginal rate t, $0 < t < 1$. Taxpayer i chooses to declare income $D_{ij} \in [0, W_{ij}]$ from source $j = L, N$, and evades the amount $Z_{ij} = W_{ij} - D_{ij}$. All deterrence parameters are identical for the two sources of incomes, so that the only difference between the two incomes arises from their source. This allows for a sharp test of mental accounting that may be difficult with field data. Irrespective of the source of income, the declaration decision of taxpayers is audited with probability $p(D) \in [0, 1]$ such that

$$p(D) = a - bD; \; a, b \geq 0. \tag{2.1}$$

From (2.1), greater evasion increases the audit probability. An audit provides observable and verifiable information to the tax authorities on the true income of the taxpayer. If caught, a tax evader must pay the outstanding tax liabilities $t(W_{ij} - D_{ij})$, and a penalty $\theta t(W_{ij} - D_{ij})$, where θ is the *penalty rate* on evaded taxes.[13] Thus, in the event of being caught, the taxpayer pays the following amount to the tax authorities

$$t(1 + \theta)(W_{ij} - D_{ij}) \equiv tf(W_{ij} - D_{ij}), \text{ where } f = 1 + \theta. \tag{2.2}$$

We call f the *fine rate*. If taxpayer i evades taxes on income source $j = L, N$, he faces morality costs $c_{ij} \in [\underline{c}, \overline{c}]$ in monetary units per unit of evaded taxes, *irrespective of whether he is caught or not*. We assume that (i) morality costs per unit are non-negative ($\underline{c} \geq 0$), and (ii) no higher than the tax rate

$$\overline{c} \leq t. \tag{2.3}$$

[12] Our framework differs from Dhami and al-Nowaihi (2007) in that they do not consider either mental accounting or the moral costs of evasion. Furthermore, their interest was not in the experimental testing of their predictions, but in simulation results with non-experimental data.

[13] If $\theta < 0$, then the government effectively subsidizes tax evasion. In our experiments, we show that for $\theta = -1$, there is significant declared income, which reveals underlying moral costs of evasion. However, our main case is $\theta \geq 0$.

Condition (2.3) is purely technical and ensures that the objective function is real-valued and not an imaginary number.[14]

Denote by $s = C,\ NC$ the state of the world, where the taxpayer is, respectively, *caught* evading taxes (C), and *not caught* evading taxes (NC). The state-contingent income Y_{ij}^{s} is:

$$Y_{ij}^{NC} = W_{ij} - tD_{ij} - c_{ij}(W_{ij} - D_{ij}),\ i \in M,\ j = L, N. \tag{2.4}$$

$$Y_{ij}^{C} = (1-t)\,W_{ij} - \theta t(W_{ij} - D_{ij}) - c_{ij}(W_{ij} - D_{ij}),\ i \in M,\ j = L, N. \tag{2.5}$$

2.2 Prospect theory value function

For reasons discussed in the introduction, we use prospect theory in our analysis. In prospect theory, taxpayers are either in the *domain of gains* (income greater than reference point), or in the *domain of losses* (income lower than the reference point). The status-quo provides a powerful reference point for both humans, animals, and plants (Kahneman and Tversky, 1979; Kahneman and Tversky, 2000; Dhami, 2019, Vol. 1). Furthermore, the legal framework (e.g., legal tax liabilities) also provides a useful reference point and enhances the status-quo in applications (Dhami and al-Nowaihi, 2007, 2010).[15] For this reason, we define the reference income, R_{ij}, of taxpayer i from income source j to be the legal after-tax income

$$R_{ij} = (1-t)W_{ij};\ i \in M,\ j = L, N. \tag{2.6}$$

Legal tax liabilities are salient and perform a role as an institutionally mandated status-quo interpretation of reference points. However, there is an even more important justification that we state separately as Remark 1 below. Denote the state-contingent income relative to the reference point by $X_{ij}^{s} = Y_{ij}^{s} - R_{ij}$, $s = C,\ NC$, where Y_{ij}^{s} is defined in (2.4), (2.5). Using (2.4), (2.5), (2.6), and recalling that $0 \leq D_{ij} \leq W_{ij}$, we get for all D_{ij} :

$$X_{ij}^{NC} = (t-c)\,(W_{ij} - D_{ij}) \geq 0;\ i \in M,\ j = L, N \tag{2.7}$$

$$X_{ij}^{C} = -\,(\theta t + c)\,(W_{ij} - D_{ij}) \leq 0;\ i \in M,\ j = L, N. \tag{2.8}$$

Remark 1 *: If the taxpayer is always in the domain of gains or always in the domain of losses (which might occur with any reference point other than the one in (2.6); see Lemma 1, below), then prospect theory reduces to rank dependent utility.*[16] *But Eide et al. (2011) showed*

[14] There might be additional psychological costs such as the stigma suffered by a tax evader in the event that the tax evader is caught (Andreoni et al., 1998; Slemord and Yitzhaki, 2002; Dhami and al-Nowaihi, 2007; Alm 2019). Such costs can be introduced within our framework, but add no substantive insights, so we have omitted them.

[15] Reference points based on fairness norms or other social norms are likely to play a major role in many phenomena (Dhami, 2019, Vol. 1). In our experiments, we provide no historical data on norms, or on the pre-requisites for such norms (Dhami, 2019, Vol. 2, Section 5.7), hence, reference points in this category are unlikely to play a role in our results. Finally, reference points based on rational expectations, sometimes known as endogenous reference points, are cognitively too complex and sit uneasily with the evidence on bounded rationality. Furthermore, there is no empirical evidence that shows that reference points are rational expectations, although expectations may play a role in their formation; see Dhami (2019, Vol. 1, Section 2.8.3).

[16] Rank dependent utility shares features with both expected utility and prospect theory. It shares the utility function with expected utility and the decision weights with prospect theory. In particular, it does not allow for reference points, hence, it has no domains of gains and losses (Dhami, 2019, Vol. 1, Section 2.3).

that the paradoxical comparative static results of the Allingham-Sandmo-Yitzhaki model carry over to rank dependent utility. All these paradoxical results can be accounted for by a prospect theory model where the reference point is as given in (2.6) (Dhami and al-Nowaihi, 2007, 2010). Therefore, the only interesting case is that in which the taxpayer is in the domain of gains if not caught, $s = NC$, but in the domain of losses if caught, $s = C$. Our assumptions guarantee that for all D_{ij}, we have $X_{ij}^{NC} \geq 0$ and $X_{ij}^{C} < 0$.

A potential tax evader $i \in M$ who has income W_{ij}, $j = L, N$, faces the following *lottery in incremental form* under prospect theory[17]

$$L_{ij} = \left(X_{ij}^{C}, p; X_{ij}^{NC}, 1-p\right);\ i \in M,\ j = L, N. \tag{2.9}$$

We use the prospect theory utility function, $v : \mathbb{R} \to \mathbb{R}$ (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), which has axiomatic foundations (al-Nowaihi et al., 2008):

$$v(X_{ij}^{s}) = \begin{cases} \left(X_{ij}^{s}\right)^{\gamma_{ij}} & if \quad X_{ij}^{s} \geq 0 \\ -\lambda_{ij}(-X_{ij}^{s})^{\gamma_{ij}} & if \quad X_{ij}^{s} < 0 \end{cases};\ s = C, NC,\ i \in M,\ j = L, N, \tag{2.10}$$

where $\gamma_{ij} \geq 0$ and $\lambda_{ij} > 0$ are preference parameters; the evidence indicates that the median values are $\gamma_{med} \approxeq 0.88$, $\lambda_{med} \approxeq 2.25$ (Dhami, 2019, Volume 1).[18] We allow λ_{ij} to vary between taxpayers and between the two sources of incomes. Following Chapman et al. (2019), a taxpayer is *loss averse* if $\lambda_{ij} > 1$ and *loss tolerant* if $\lambda_{ij} < 1$.

In Sections 1.1, 1.2 in the introduction, we have discussed evidence for the result that earned labor income creates greater entitlements relative to unearned non-labor income. Our hypothesis is that entitlements manifest through the following two channels.

1. Lower moral cost of evading labor income relative to non-labor income.

$$c_{iL} < c_{iN} \text{ for all } i \in M. \tag{2.11}$$

2. Higher loss aversion from labor income relative to non-labor income.

$$\lambda_{iN} < \lambda_{iL};\ \text{for all } i \in M. \tag{2.12}$$

Notation: : Although the notation with the ij subscripts is the clearest, it is also cumbersome. Throughout the paper, we will be analyzing a particular taxpayer (some $i \in M$) who has a particular source of income (W_j, $j = L, N$). Hence, we dispense with the ij subscripts and speak of a generic taxpayer with income W, reference point R, morality cost c, and loss aversion parameter λ. We also use X^{NC} instead of X_{ij}^{NC}, and X^{C} instead of X_{ij}^{C}.

[17] Lotteries in prospect theory, sometimes known as prospects, are expressed such that the reference point is subtracted from each outcome. Such lotteries are therefore also known as lotteries in incremental form (Dhami, 2019, Vol. 1, Section 2.4).

[18] If $\gamma \in [0, 1]$, then it is straightforward to show that the utility function is concave in gains and convex in losses. To be sure, the power coefficient in gains and losses may be different but the weight of the evidence suggests that this coefficient is statistically indistinguishable in gains and losses. Furthermore, there can be substantial heterogeneity in the parameter of loss aversion and it may also be context, age, and mood dependent. For the empirical evidence, see Dhami (2019, Vol. 1). See Section 6.2 below for further discussion on the estimated size of loss aversion.

Non-linear probability weighting is an important feature of prospect theory. However, we shall assume linear probabilities in our main model.[19] Since there is one outcome each in the domain of gains and losses (see (2.7), (2.8)), the prospect theory utility of the lottery L in (2.9) is

$$V = (1 - p(D))v\left(X^{NC}\right) + p(D)\, v\left(X^{C}\right). \tag{2.13}$$

where X^C, X^{NC} are defined in (2.7), (2.8) and v in (2.10).

Define the vector of parameters for any taxpayer by

$$\phi = (\theta, t, a, b, \gamma, c, \lambda). \tag{2.14}$$

As noted above, we omit the indices i, j for notational clarity.[20]

Next we show that $R = (1-t)W$ is the unique reference point such that, for all $D \in [0, W]$, an individual is in the domain of losses if caught evading and in the domain of gains if not caught.

Lemma 1 : *Consider an arbitrary reference point R. Suppose that for all levels of declared income, $D \in [0, W]$, a tax payer is in the domain of gains if not caught, $X^{NC} \geq 0$, but in the domain of losses if caught, $X^C \leq 0$. Then, the reference point must, necessarily, be $R = (1-t)W$.*

3 The optimization problem and results

Substituting (2.7), (2.8), (2.10) in (2.13), we get the optimization problem of the taxpayer:

$$D^* \in \underset{<D\in[0,W]>}{\arg\max}\ V(D,\phi) = (W - D)^\gamma \left[(1 - p(D))(t-c)^\gamma - p(D)\,\lambda\,(\theta t + c)^\gamma\right], \tag{3.1}$$

where $\phi = (\theta, t, a, b, \gamma, c, \lambda)$ is given in (2.14).[21] From (3.1), and using (2.1) to get $p'(D) = -b$, we have

$$\begin{aligned} \frac{\partial V}{\partial D} &= (t-c)^\gamma \left[-(1-p(D))\gamma (W-D)^{\gamma-1} + b(W-D)^\gamma\right] \\ &\quad -\lambda(\theta t + c)^\gamma \left[-p(D)\,\gamma\,(W-D)^{\gamma-1} - b(W-D)^\gamma\right]. \end{aligned} \tag{3.2}$$

Proposition 1 *(a) A solution $D^*(\phi) \in [0, W]$ to the problem in (3.1) exists.*
(b) Whenever the solution is an interior solution, $D^* \in (0, W)$, it is the unique interior solution. For all $z \in \phi$, where ϕ is given in (2.14), the sign of $\frac{\partial D^*}{\partial z}$ is that of $\frac{\partial^2 V}{\partial D \partial z}$.

[19] Our comparative static results generalize to non-linear probability weights but at an increased cost of algebraic complexity without generating any new insights. However, if one's interest lies in explaining the quantitative tax evasion puzzles, then non-linear probability weights are required (Dhami and al-Nowaihi, 2007, 2010) but the simulations then need to be carried around linearized models.

[20] In order to capture preference heterogeneity, (2.14) written in full notation in our model is

$$\phi_{ij} = (\theta, t, a, b, \gamma_{ij}, c_{ij}, \lambda_{ij})\,;\ i \in M,\ j = L, N.$$

[21] The term $(t-c)^\gamma$ in (3.1) shows why the technical assumption in (2.3), $\bar{c} \leq t$, was necessary to ensure that the objective function is real valued.

Proposition 1a shows that we can proceed with a formal analysis of the comparative static effects. Proposition 1b gives an intermediate result that simplifies the derivation of comparative static results.

3.1 Comparative Statics

We now give the comparative static results in Proposition 2 for an interior solution that requires $b > 0$ (see (2.1)), i.e., the probability of detection is increasing in the amount evaded.[22] We then provide a discussion of the results.

Proposition 2 *Consider an interior solution to optimal declared income* $D^* \in (0, W)$ *and* $b > 0$.
(a) (Effectiveness of deterrence) D^* *is increasing in the penalty rate, i.e.,* $\frac{\partial D^*}{\partial \theta} > 0$. *An increase in the exogenous probability of detection,* a, *increases* D^* *i.e.,* $\frac{\partial D^*}{\partial a} > 0$.[23]
(b) (Loss aversion reduces evasion) D^* *is increasing in the parameter of loss aversion,* λ, *i.e.,* $\frac{\partial D^*}{\partial \lambda} > 0$.
(c) (Explanation of Yitzhaki puzzle) D^* *is decreasing in the tax rate, i.e.,* $\frac{\partial D^*}{\partial t} < 0$.
(d) (Morality costs) D^* *is increasing in the morality costs from evasion,* c, *i.e.,* $\frac{\partial D^*}{\partial c} > 0$.

For completeness, the next proposition considers the two boundary solutions $D^* \in \{0, W\}$.

Proposition 3 *(a) Let* $\widehat{a} = \left(1 + \frac{\lambda(\theta t + c)^\gamma}{(t-c)^\gamma}\right)^{-1} - \frac{1}{\gamma} bW$ *and* $b > 0$. *Then, for* $D \in [0, W)$, $D^* = 0$ *is optimal if* $\widehat{a} > 0$ *and the exogenous probability of detection,* a, *is low enough in the sense that* $a < \widehat{a}$.
(b) At an optimum on the boundary ($D^* = 0$ *or* $D^* = W$), D^* *is non-increasing in* a, b, c, θ, λ. *However,* D^* *is non-decreasing in the tax rate,* t.

Discussion of the results: From Proposition 2(a), an increase in the probability of detection increases the probability that the tax evader receives lower income (state $s = C$), thus reducing the marginal returns from evasion, which reduces evasion. An increase in the audit penalty, θ, reduces income in the state $s = C$, hence the marginal returns from evasion, which reduces evasion. Identical results arises under expected utility and rank dependent utility. An increase in loss aversion increases the losses that arise in the state $s = C$, when caught evading taxes, reducing the marginal returns from evasion, hence, reducing evasion (Proposition 2b). From Proposition 2c, prospect theory predicts that as the tax rate increases, evasion increases, in conformity with the evidence, so there is no Yitzhaki puzzle under prospect theory; this is an extension of the result in Dhami and al-Nowaihi (2007) to mental accounting.[24] Finally, an increase in the moral cost, c, of tax evasion reduces evasion (Proposition 2d). An increase in c

[22] In Section 3.2 and Proposition 3 we discuss the case of an exogenous probability of detection, i.e., $b = 0$.

[23] An increase in b, the variable probability of detection in the function $p(D) = a - bD$, has an ambiguous effect on D^*. It can be shown that if $W \geq D^*(1 + \gamma)$ then D^* is increasing in b, otherwise it is decreasing in b. However, we are not interested in this comparative static result.

[24] Under expected utility theory and decreasing absolute risk aversion an increase in the tax rate reduces evasion, which is counterintuitive (Yitzhaki, 1974). This contradicts most available evidence; see Andreoni et al. (1998); Slemrod and Yitzhaki, 2002; and Alm (2019).

reduces each of X^{NC} and X^C by one unit. However, the unit reduction in the domain of losses is weighted by the loss aversion parameter, which reduces the marginal utility of income in the state $s = C$ relatively more, as compared to the state $s = NC$. Hence, optimal evasion falls.

Proposition 3(a) can be stated in many different ways by placing an upper bound on different exogenous variables. We have found it convenient to state it in terms of an upper bound on the exogenous probability of detection, a. If a is low enough ($a < \widehat{a}$ and $\widehat{a} > 0$), then there is insufficient deterrence to prevent the taxpayer from evading all income.

3.2 Results with an exogenous probability of detection

Section 3.1 considered the case $p(D) = a - bD$, $b > 0$. Now suppose that $b = 0$, so that $p(D) = a$ is independent of D. In experiments, the case $p(D) = a$ is the clearest to implement when other parameters such the exogenous probability, a, the tax rate, t, and the penalty rate, θ, are varied.[25] Substitute $p(D) = a$ in (3.1) to get

$$D^* \in \underset{<D\in[0,W]>}{\arg\max}\ V(D,\phi) = (W-D)^{\gamma} h(\phi), \tag{3.3}$$

where ϕ is given in (2.14) and

$$h(\phi) = \left[(1-a)(t-c)^{\gamma} - a\lambda(\theta t + c)^{\gamma}\right]. \tag{3.4}$$

We have a corner solution in this case. If $h(\phi) < 0$ then $V(D,\phi)$ attains a maxima if the term $(W-D)^{\gamma}$ is as small as possible, so $D^* = W$. The opposite, $D^* = 0$, occurs if $h(\phi) > 0$. If $h(\phi) = 0$ we have a continuum of solutions, $D^* \in [0,W]$. Summarizing:

$$D^* = \begin{cases} W & if \quad h(\phi) < 0 \\ [0,W] & if \quad h(\phi) = 0 \\ 0 & if \quad h(\phi) > 0 \end{cases}. \tag{3.5}$$

The comparative static properties are similar to those in Proposition 2 for the case $b > 0$, except that they take the form of threshold rules, as shown in the next proposition.

Proposition 4 : *Suppose that the probability of detection is independent of the evaded amount, so that $p(D) = a > 0$ (and $b = 0$) for all $D \in [0,W]$. Let D^* be the optimal level of declared income.*

(a) (Exogenous probability of detection, a) Let $a \in [0,1]$. Then there exists a critical value of $a = a_c > 0$ such that if $a < a_c$, $D^* = 0$, and if $a > a_c$, $D^* = W$. When $a = a_c$, we have $D^* \in [0,W]$.

(b) (Penalty rate, θ) Let $\theta \in [0,\overline{\theta}]$, where $\overline{\theta}$ is the maximum possible penalty rate. Then there exists a critical value of $\theta = \theta_c > 0$ such that when $\theta < \theta_c$, $D^* = 0$, and when $\theta > \theta_c$, $D^* = W$. When $\theta = \theta_c$, we have $D^* \in [0,W]$.

(c) (Tax rate, t) There exists a critical value of the tax rate $t_c > 0$ such that for all $t < t_c$, $D^* = W$, and for $t > t_c$, $D^* = 0$. When $t = t_c$, we have $D^* \in [0,W]$.

(d) (Loss aversion) There exists a critical value of the parameter of loss aversion $\lambda_c > 0$ such that if $\lambda < \lambda_c$, then $D^* = 0$, and if $\lambda > \lambda_c$, then $D^* = W$. When $\lambda = \lambda_c$, we have $D^* \in [0,W]$.

[25] In our experiments, we implement both cases, $b > 0$ and $b = 0$.

The intuition behind the results in Proposition 4 is identical to that for Proposition 2, which has been already discussed above.

Remark 2 : *One implication for testing the predictions of Proposition 4 comes from the 'threshold nature' of results. A change in any of the exogenous parameters of the models, may lead to "stickiness" of the optimal declared income, until the exogenous parameter crosses the threshold value either from above or from below.*

3.3 Treatment effects

What is the effect on declared income D^* as we move from Treatment T1 (earned labor income) to Treatment T2 (unearned non-labor income)? Recall from (2.11) and (2.12) that the movement from T1 to T2 is hypothesized to cause changes in the loss aversion parameter, λ, and in the morality cost, c, from tax evasion. By assumption, $c \in [\underline{c}, \overline{c}]$ and $\lambda \in [0, \overline{\lambda}]$, where $\overline{\lambda} \in \mathbb{R}_+$ is an upper limit to the loss aversion parameter. Consider now the two-dimensional space $S = [\underline{c}, \overline{c}] \times [0, \overline{\lambda}] \subset \mathbb{R}^2$. Treatment 1 corresponds to a tuple $s_1 = (c_1, \lambda_1) \in S$ and Treatment 2 to another tuple $s_2 = (c_2, \lambda_2) \in S$. Hence, we need to consider directional derivatives to answer the question posed at the beginning of this paragraph.

Consider a vector of unit length $u \in S$. We define u by normalizing the vector s_2 so that it has unit length.[26] Then, the set of all vectors of the form $z(\tau)$ such that

$$z(\tau) = s_1 + \tau u, \, \tau \in \mathbb{R},$$

give rise to the straight line from the point s_1 in the direction u (or s_2) such that τ is the distance from s_1 to z along this line. Thus, starting from s_1 (Treatment 1) we move towards s_2 (Treatment 2) in a straight line by varying the parameter τ.

Using (3.2), the first order condition for an interior optimum can now be implicitly written as:

$$\frac{\partial V(D(\tau), c(\tau), \lambda(\tau), .)}{\partial D} = 0. \tag{3.6}$$

Since V is a twice continuously differentiable function, hence, $D(\tau), c(\tau), \lambda(\tau)$ are continuously differentiable functions of τ. Implicitly differentiating (3.6) with respect to τ we get

$$\frac{dD}{d\tau} = \left(-\frac{\partial^2 V}{\partial D^2}\right)^{-1} \left[\alpha_1 \frac{dc}{d\tau} + \alpha_2 \frac{d\lambda}{d\tau}\right], \; \alpha_1 = \frac{\partial^2 V}{\partial D \partial c}, \; \alpha_2 = \frac{\partial^2 V}{\partial D \partial \lambda}. \tag{3.7}$$

From the proof of Proposition 1, we know that the second order condition holds strictly. Thus, the sign of $\frac{dD}{d\tau}$ is determined by the sign of the term in the square brackets. We know $\alpha_1 > 0$ (Proposition 2d) and $\alpha_2 > 0$ (Proposition 2b).

From (2.11) and (2.12), as we move from T1 to T2, $\frac{dc}{d\tau} > 0$ (moral costs rise) and $\frac{d\lambda}{d\tau} < 0$ (loss aversion falls). Thus, the two terms in the square brackets in (3.7) have the opposite signs. Therefore, the sign of $\frac{dD}{d\tau}$ is an empirical matter. We summarize the implications in the following Remark, which is important to understand our assumptions and results..

[26]The vector $u = \left(\frac{c_2}{\|s_2\|}, \frac{\lambda_2}{\|s_2\|}\right)$.

Remark 3 : *The treatment effect is the difference in average declared amounts (or evaded amounts, through the relation $Z = W - D$) between Treatment 1 and Treatment 2, as shown in (3.7). Since the effects of loss aversion and moral costs oppose each other, depending on the relative strengths of the two effects, the treatment effect can be positive, zero, or negative. Indeed, even if the overall treatment effect is weak or non-existent, it could be that the effects of loss aversion and moral costs roughly balance out in opposite directions.*

*In our empirical analysis (Section 8 below) we find (i) the treatment effects are negative (lower evasion in Treatment 1) but significant only at 10%, and (ii) a "strong" negative effect of loss aversion that is significant at 1% (loss aversion reduces evasion). Further, we find median loss aversion to be higher in Treatment 1 relative to treatment 2 (*1.82 *vs* 1.53*; see Section 6.2). On the face of it, this should account for our data (higher loss aversion in Treatment 1 and lower evasion). However, there are two counterarguments:*

(1) Since the treatment effect is weak but the effect of loss aversion is strong, this is suggestive of another effect on evasion in the opposite direction, as formalized in our second conjecture in (2.11), i.e., lower moral costs in Treatment 1 that induce greater evasion of labor income. We demonstrate the existence of moral costs in our data (significant levels of declared incomes even when there is a 100% subsidy to evasion; see Section 7.2). However, we do not measure income-specific moral costs and it is not known how one might measure such costs, which probably requires advances in neuroscience. Hence, our results can only provide indirect evidence for income-specific moral costs, but not definitive proof.[27] *We do not also rule out the possibility that moral costs may reflect deeper underlying moral norms.*

(2) The importance of moral costs in illegal activity has been highlighted by the evidence in behavioral economics (see the introduction), and such costs are pervasive in the theoretical literature on tax evasion (Slemrod and Yitzhaki, 2002; Slemrod, 2018; Alm, 2019). Hence, it would appear unsuitable to ignore them.

4 Measuring loss aversion and risk aversion

We split the discussion in this section into (1) the theory behind our elicitation of loss aversion, based on a *lottery choice task*, that is separate from the tax evasion task, and (2) the *bisection method* for the practical measurement of loss aversion that closely follows Abdellaoui (2000) and has been used since in several studies. We also compute the *risk attitudes* of subjects.

4.1 Theoretical framework for estimating loss aversion

Suppose that the income of the subject is y, which could either be in Treatment 1 or 2. We assume that the reference income, r, of the subject is the status-quo income, so $r = y$ (and this is made fairly salient in the experimental instructions). We fix an outcome $z > 0$ and a probability $p > 0$ and then elicit the value of the outcome $x > 0$ for which a subject expresses

[27]This is not unusual in the natural sciences. For instance, the standard method to demonstrate that a distant star has an orbiting planet is to try to detect a slight wobble in the orbit of the star caused by gravity, although the orbiting planet is never directly observed.

the following indifference between two lotteries:

$$L_1 \sim L_2, \text{ where } L_1 = (y, 1), \ L_2 = (y - z, p; y + x, 1 - p). \tag{4.1}$$

We can now evaluate L_1 and L_2 using prospect theory. Only for this calculation, do we allow for non-linear probability weighting, in order to show the robustness of our results to non-linear weighting. A probability weighting function is a strictly increasing function $w : [0, 1] \overset{onto}{\to} [0, 1]$.[28]

$$V(L_1) = v(y - r) = 0 \text{ [Using } r = y \text{ and } v(0) = 0]$$

$$\begin{aligned} V(L_2) &= w(p)v(y - z - r) + w(1 - p)v(y + x - r) \text{ [Using prospect theory]} \\ &= w(p)v(-z) + w(1 - p)v(x) \text{ [Using } r = y] \\ &= -\lambda(z)^\gamma w(p) + x^\gamma w(1 - p) \text{ [Using 2.10)].} \end{aligned}$$

Thus, the indifference in (4.1) implies that $0 = -\lambda(z)^\gamma w(p) + x^\gamma w(1 - p)$, so

$$\lambda = \left(\frac{w(1 - p)}{w(p)}\right)\left(\frac{x}{z}\right)^\gamma. \tag{4.2}$$

In particular, for the case $p = 0.5$, that we use in our experimental design, we have $w(1 - p) = w(p) = w(0.5)$, hence, from (4.2) we have that the parameter of loss aversion is

$$\lambda = \left(\frac{x}{z}\right)^\gamma. \tag{4.3}$$

Remark 4 : *(a) The elicitation in this section is carried out for each individual taxpayer $i \in M$ and separately for each treatment, which varies the source of income $j = L, N$. Hence, (4.3) written in full notation is*

$$\lambda_{ij} = \left(\frac{x_{ij}}{z}\right)^{\gamma_{ij}}; \ i \in M, \ j = L, N. \tag{4.4}$$

Once we have elicited x on the RHS of (4.3) (see Section 4.2 below), we need to approximate the preference parameter, γ, of a subject with income y (see Section 4.3 below).

For the calculation of γ, we elicit the certainty equivalent value C such that a subject exhibits the following indifference

$$C \sim (y, 0.5; 2y, 0.5). \tag{4.5}$$

The lottery $(y, 0.5; 2y, 0.5)$ offers a 50-50 chance of "keeping the status-quo income y" or "doubling the status-quo income y" (indeed, such framing, which we use in the experimental instructions, makes the status-quo income salient). Thus, reference income equals the status-quo income y $(r = y)$. It is reasonable to suppose that $C \in [y, 2y]$. Estimating the indifference in (4.5) implies the following cumulative prospect theory calculation

$$\begin{aligned} v(C - y) &= [1 - w(0.5)]\, v(y - y) + w(0.5)v(2y - y) \\ &\Rightarrow v(C - y) = w(0.5)v(y) \text{ [Using } v(0) = 0]. \end{aligned} \tag{4.6}$$

[28]We only require a basic understanding of the evaluation of lotteries under non-linear probabilities. For the details see Dhami (2019, Vol. 1, Sections 2.2, 2.4) or Wakker (2010).

Using (2.10) and the approximation $w(0.5) \approx 0.5$ (see Remark 5, below), (4.6) implies the following approximation for γ that we use in our estimates.

$$\gamma \approx \frac{\log(0.5)}{\log\left(\frac{C-y}{y}\right)}. \tag{4.7}$$

Remark 5 *: The Prelec probability weighting function $w(p) = e^{-\beta(-\ln p)^{\alpha}}$, where $\alpha, \beta \geq 0$, has good empirical support and has axiomatic foundations (Prelec, 1998; al-Nowaihi and Dhami, 2006). Bruhin et al.'s (2010) mixture model estimates of the median values are $\beta = 0.8$ and $\alpha = 0.45$ (this value of α is also consistent with the simulations in Dhami and al-Nowaihi, 2007). Evaluated at these parameter values, $w(0.5) = e^{-0.8(-\ln 0.5)^{0.45}} = 0.507$. Estimating α, β for each subject is a cognitively taxing and time consuming process, and more suited to a lab experiment (for details, see Dhami, 2019, Vol. 1, Section 2.5.3). For this reason, we have used the approximation $w(0.5) \approx 0.5$ in (4.7).*

4.2 Estimation of x using the bisection procedure

In this section we outline how we estimate x in (4.3). Consider the two lotteries L_1 and $L_2(x)$ in (4.1), where y, z, and p are fixed. Our objective is to find the loss aversion parameter after offering a series of 6 lottery choices.

1. Choice 1: Subjects are given a choice between $L_1 = (y, 1)$ and $L_2(x_1) = (y - z, 0.5; y + x_1, 0.5)$, where x_1 is determined by equating the expected value of the two lotteries, so $y = 0.5(y - z) + 0.5(y + x_1)$. Thus, $x_1 = z$.
   (1.1) If $L_2(x_1)$ is chosen over L_1 we make $L_2(x_1)$ less attractive in the next step by reducing $x_1 = z$ to $x_2 = \frac{z}{2}$, which is the midpoint of $[0, z]$ (we bisect the interval in each choice, hence, the name 'bisection procedure').
   (1.2) If L_1 is chosen over $L_2(x_1)$, then we make the lottery L_2 more attractive by increasing $x_1 = z$ to $x_2 = 3z$ which is the midpoint of the interval $[z, 5z]$; the upper limit $5z$ is picked to be arbitrarily high to accommodate even extreme preferences.

2. Choice 2: Subjects are given a choice between $L_1 = (y, 1)$ and $L_2(x_2) = (y - z, 0.5; y + x_2, 0.5)$, where x_2 is determined from Choice 1.
   (2.1) If $L_2(x_2)$ is chosen over L_1 we make $L_2(x_2)$ less attractive by reducing x_2 to x_3 that is the midpoint of $[0, x_2]$.
   (2.2) If L_1 is chosen over $L_2(x_2)$, then we make L_2 more attractive by increasing x_2 to x_3 which is the midpoint of the interval $[x_2, 5z]$.

3. Choice $k = 3, 4, 5$: Subjects choose between $L_1 = (y, 1)$ and $L_2(x_k) = (y-z, 0.5; y+x_k, 0.5)$, where x_k is determined from Choice $k - 1$.
   (3.1) If $L_2(x_k)$ is chosen over L_1, x_k is reduced to $x_{k+1} = \frac{x_k}{2}$.
   (3.2) If L_1 is chosen over $L_2(x_k)$, x_k is increased to $x_{k+1} = \frac{x_k+5z}{2}$.

4. Choice 6: Subjects choose between $L_1 = (y, 1)$ and $L_2(x_6) = (y - z, 0.5; y + x_6, 0.5)$, where x_6 is determined from Choice 5.

(4.1) If $L_2(x_6)$ is chosen over L_1, then the required value of x in (4.3) is $x = \frac{1}{2}(x_6)$.

(4.2) If L_1 is chosen over $L_2(x_6)$, then, the required value of x in (4.3) is $x = \frac{1}{2}(x_6 + 5z)$.

4.3 Estimation of γ using the bisection procedure

In order to estimate λ in (4.3), we first need to estimate x (which was done in Section 4.3). Then, in order to approximate γ in (4.7, we elicit the value C such that the indifference in (4.5) holds. We employ the bisection method with 6 choices, as in Section 4.2. Given the similarity of the two methods, we omit a detailed description, which can be found in Dhami and Hajimoladarvish (2020). Let $L_1(c) = (c, 1)$ and $L_2 = (y, 0.5; 2y, 0.5)$ be the two lotteries in (4.5), where c is an estimate of the unknown certainty equivalent C.

1. Choice 1: Since $C \in [y, 2y]$, we pick an initial guess c_1 of C, as the midpoint of the interval $[y, 2y]$, so $c_1 = 1.5y$. The subject is offered a choice between $L_1(c_1)$ and L_2. We then update the guess c_1 to a new value c_2 for the second choice as follows. (i) If $L_1(c_1)$ is chosen over L_2, then $c_2 = \frac{y+c_1}{2}$ (i.e., the lottery L_1 is made less attractive in Choice 2). (ii) If L_2 is chosen over $L_1(c_1)$, then $c_2 = \frac{c_1+2y}{2}$ (i.e., the lottery L_1 is made more attractive in Choice 2).

2. Choice 2: The subject chooses between $L_1(c_2)$ and L_2, where c_2 is determined from Choice 1. The value c_2 is updated to a new value c_3 (used for the third choice) as follows. (i) If $L_1(c_2)$ is chosen over L_2, then $c_3 = \frac{y+c_2}{2}$ (L_1 is made less attractive). (ii) If L_2 is chosen over $L_1(c_2)$, then $c_3 = \frac{c_2+2y}{2}$ (L_1 is made more attractive).

3. Choice $k = 3, ..., 5$. The subject chooses between $L_1(c_k)$ and L_2, where c_k is determined in Choice $k - 1$. The value c_k is updated to a new value c_{k+1} for the Choice $k + 1$ as follows. (i) If $L_1(c_k)$ is chosen over L_2, then $c_{k+1} = \frac{y+c_k}{2}$ (L_1 is made less attractive). (ii) If L_2 is chosen over $L_1(c_k)$, then $c_{k+1} = \frac{c_k+2y}{2}$ (L_1 is made more attractive).

4. Choice 6: The subject is offered a choice between the lotteries $L_1(c_6)$ and L_2, where c_6 is determined from Choice 5. The final value of the certainty equivalent C, which is the objective of this elicitation exercise, is now calculated as follows. (i) If $L_1(c_6)$ is chosen over L_2, then $C = \frac{y+c_6}{2}$. (ii) If L_2 is chosen over $L_1(c_6)$, then $C = \frac{c_6+2y}{2}$.

4.4 Risk attitudes

The estimation of γ in Section 4.3 allows us to elicit data on the subject's risk attitudes as well. The reason is that we have elicited the certainty equivalent C of the lottery $L_2 = (y, 0.5; 2y, 0.5)$, and we know its expected value $EL_2 = 1.5y$. Directly comparing C with EL_2 we can determine if a subject is risk averse ($C < EL_2$) or risk loving ($C > EL_2$). In Section 4.3, we elicited attitudes to risk only in the domain of gains, and not for mixed lotteries that have both gains and losses (as, say, in Section 4.2). Hence, such elicitation of risk attitudes is independent of the parameter of loss aversion, and may be used to add to the list of control variables in our explanation of tax evasion in Section 8.

5 Experimental Design and parameterization

Our experiments were originally scheduled to be run in the economics lab in the School of Economics, Nottingham University, in March 2020. Unfortunately, just as we got ready to run the experiments, all British Universities were abruptly shut down due to Covid19. We were then offered a chance to run the experiments online on MTurk with US subjects, under the aegis of Nottingham University in June 2020, which we accepted.[29] MTurk has several advantages and disadvantages relative to University lab experiments.[30]

We gave \$2 as participation fee, \$2 for completing the task, and a further incentive payment based on choices during the experiment. On average, it took subjects 18 minutes to complete the task, and the average payment per subject was \$5.38; thus, the per hour payment, on average, was \$17.93.[31] Subjects were assured that their responses would be kept anonymous and were for research purposes only. Several illustrative examples were given to the subjects to enhance their understanding of the experiments. Subjects also had to answer test questions correctly to proceed in the experiment. These questions were also designed to prevent bots from attempting the experiment.

We used a between-subjects design to derive the contrast between our two treatments. Subjects are randomly allocated to one of the two treatments.[32] In Treatment 1, subjects could earn labor income by performing a tedious task that required them to count the number of 7s and 9s in sequences of densely packed numbers in 150 seconds. Based on the number of correct answers, subjects could earn one of the following labor income levels: 50, 100, 150, 200, or 250. Our pilot results indicated that earning a labor income level of 250 was rare. Thus, in order to keep the frequency of subjects for each income level comparable in the two treatments, in Treatment 2, we randomly allocated subjects to unearned non-labor income levels of 50, 100, 150, or 200. We did not allow subjects to participate in more than one treatment from a given IP address, but we cannot guarantee that no subject was using multiple IP addresses.

Once the income of the subjects was determined (Task 1), they participated in two main tasks (Tasks 2 and 3) whose order was randomized. (1) A *lottery task* that was designed to elicit their loss aversion, and (2) a *tax payment task* in which they had an opportunity to evade taxes.

The lottery task

[29]Our funding in the form of a grant from the University of Leicester came with the proviso that it needed to be spent by 31 July 2020. The online experiment was programmed in LIONESS, developed by Giamattei et al. (2020).

[30]Among the advantages are that the experiment can be run in a relatively short period of time; the subjects are more diverse, older, and more geographically representative of the US population relative to the student-lab subjects; and are more likely to have paid taxes in the past. Among the disadvantages is the possibility that professional subjects have the objective of maximizing daily earnings, which might conflict with truthful revelation of preferences. This problem is not always resolved through incentivizing tasks (see discussion below in Section 6.2). A further problem arises with bots attempting the experiments and subjects with potentially multiple IP addresses muting the variability in the data. See Robinson et al. (2019) and Sauter et al. (2020) for a survey of the pros and cons of online experiments, and the reference cited therein.

[31]All payoffs in the experiment were in units of an experimental currency, EC, that was converted to dollars at the end of the experiment, using the exchange rate 100 EC = 1 Dollar.

[32]At the beginning of experiment, subjects were allocated to either of the two treatments based on a unique number allocated to each participant (even numbered subjects participated in Treatment 1 and odd numbered subjects participated in Treatment 2).

The lottery task was conducted using the income of the subjects from Task 1 (labor income in Treatment 1 and non-labour income in Treatment 2). The elicitation of the loss aversion is implemented using the process described in Section 4.

The tax payment task

Using either their labor income (Treatment 1) or non-labor income (Treatment 2), we asked subjects to declare their income for tax purposes in response to the following 7 questions. The order of these questions was not randomized. The total number of possible random orders of 7 questions is 5040, which exceeds the number of subjects.

1. Questions 1-3 (Q1, Q2, Q3) ask subjects to declare their income for different values of the tax rate (5%, 30%, 60%). The audit probability is held fixed at 3% and the fine rate at $f = 2$, where $f = 1 + \theta$ is defined in (2.2); these are empirically realistic magnitudes for an amateur tax evader (Slemrod and Skinner, 1987).

2. Questions 4-6 (Q4, Q5, Q6) ask subjects to declare their income for different values of the fine rate $f = 1 + \theta$ (0, 2, 3). We hold fixed the audit probability at 3% and the tax rate at 30%. When $f = 2$, the effective penalty rate is $\theta = 1$ (tax evaders who are caught pay back owed taxes and an identical further amount as penalties), and when $f = 3$ the effective penalty rate $\theta = 2$. The case $f = 0$ corresponds to $\theta = -1$, i.e., a 100% subsidy to the taxpayer from evasion so, if caught evading, the taxpayer pays nothing, not even owed taxes. If taxpayers face no monetary consequences for evasion, yet if they declare any taxes, then moral costs of tax evasion are the prime candidate explanation.

3. Question 7 (Q7) asks subject to declare their income when the probability of audit is increasing in evaded income. In terms of the audit probability function in (2.1), $a > 0, b > 0$ for Q7, while for Q1-6, we have $a > 0, b = 0$. The fine rate is held fixed at $f = 2$ and the tax rate at 30%. In particular, we use the parametrization

$$p(D) = 0.08 - 0.0002D, \tag{5.1}$$

so $a = 0.08$ and $b = 0.0002$. Thus, starting with an exogenous probability of detection of 8%, for every increase in declared income, D, of 50, the probability of detection decreases continuously by 1%. As an example, for someone with an income of 250, who declared his entire income, the detection probability is 3%. For most amateur tax evaders, the detection probability ranges between 1% to 5% (Slemrod and Skinner, 1985).

Since the probability of detection is kept fixed for Q1-Q6, the relevant predictions of our model are contained in Proposition 4. Q7 enables us to test the prediction of our more general model (see Proposition 2) based on an audit probability that is increasing in the amount evaded.

6 Data description and measurement of loss aversion

In this section, we first give general descriptive statistics, followed by our estimates of loss aversion and risk aversion.

6.1 Descriptive statistics

Out of 588 people who started the experiment, 276 people managed to complete it. For 7 subjects we have some NAs which are due to bots attempting the experiment, and for another 23 subjects declared taxes were more than their income, which is not feasible. Dropping these individuals, we have a sample size of 246.

Table 1: Frequency of subjects in each income category for each treatment

Treatments	Income levels	50	100	150	200	250	mean	median
Labour (n=124)	Frequencies	42	13	21	34	14	135	150
Non-Labour (n=122)	Frequencies	53	9	25	35	-	117	100

The number of subjects in each category of income (50, 100,..., 250) for Treatment 1 (labor income) and Treatment 2 (non-labor income) is shown in Table 1. There is a roughly equal split of subjects in each treatment (124 in Treatment 1 and 122 in Treatment 2). There are no subjects with an income of 250 in Treatment 2.[33] The mean and median of income, weighted by the proportion of subjects in each income category, is relatively higher for non-labor income.

Table 2: Percentage of declared income for each treatment

		Q1	Q2	Q3	Q4	Q5	Q6	Q7
Percentage of declared labour income	Mean	50	35	34	31	32	43	51
	median	45	30	25	0	15	40	50
Percentage of declared non-labour income	Mean	51	38	33	31	34	49	54
	median	50	30	33	0	18	50	60

Table 3: Number of corner solutions by source of income

		Q1	Q2	Q3	Q4	Q5	Q6	Q7
Labour income	D=W	48 (38%)	18 (15%)	17 (14%)	26 (21%)	20 (16%)	28 (23%)	35 (28%)
	D=0	26 (21%)	34 (27%)	40 (32%)	69 (56%)	48 (39%)	35 (28%)	32 (26%)
Non-labour income	D=W	49 (40%)	15 (12%)	9 (7%)	32 (26%)	20 (16%)	29 (24%)	35 (29%)
	D=0	26 (21%)	32 (26%)	36 (29%)	65 (53%)	44 (36%)	26 (21%)	26 (21%)

Percentage of subjects whom choose corner solutions are in parentheses.

In Table 2, we report the mean and the medians, across all subjects, in all income categories, for each of our 7 questions (see Section 5 for a description of the questions). Except for Q3 and Q4 where the average figures are nearly identical for both treatments, for every other question, people declare relatively less (i.e., evade more) labor income. Aggregated across all 7 questions,

[33] As noted earlier, based on our pilot where no subjects earned an income of 250, we omitted this category in our experimental design for non-labor income.

subjects declared 40% of their labor income, and they declared 42% of their non-labor income. The result of a t-test indicates that there is no significant difference between the percentage of declared incomes in the two treatments (p-$value = 0.354$). Furthermore, for each question, there is no significant difference between the percentage of declared incomes in each Treatment (all p-values from t-tests and Wilcoxon tests are greater than 0.2). This is consistent with our predictions, due to the opposing roles of loss aversion and moral costs of evasion (Remark 3).

A corner solution arises when a subject chooses either to declare nothing ($D = 0$) or their full income ($D = W$). Table 3 shows the incidence of corner solutions in the model (by absolute numbers and percentages) for each source of income. On average, across all 7 questions, 55% of the subject choices in Treatment 1 and 52% of the subject choices in Treatment 2 were corner solutions. Across all questions and both treatments, 22% of the subjects declared their full income and 31% declared no income, for a total of 53% corner solutions.

Recall from (3.5) in Section 3.2 that under an exogenous probability of detection (as in Q1-Q6 in our experiments), one obtains either (i) a corner solution, or (ii) the optimal choice is indeterminate, $D^* \in [0, W]$, if $h(\phi) = 0$. Hence, one interpretation of the finding of an interior solution for Q1-6 is that for such subjects, $h(\phi) = 0$. A more radical inference is that some subjects do not in fact optimize, but choose simple rules of thumb (or heuristics) in making choices.[34]

Recall that we randomized the order between Tasks 2 and 3 (lottery task and tax payment task). No order effects were found. There is no statistically significant difference in declared incomes across all 7 questions for both groups, those who faced the lottery task first and those who faced the tax payment task first; p-values from the t-tests for the 7 questions (Q1-Q7) in chronological order are 0.39, 0.62, 0.56, 0.15, 0.23, 0.22, 0.46.

6.2 Loss aversion and risk aversion

Our measurement of loss aversion is described in Section 4; see equation (4.3). Our estimate of median loss aversion is 1.73. This figure is representative of other estimates of loss aversion in the literature. Chapman et al. (2019) report median values of loss aversion between 1.5 and 2.5 in their survey of the literature. If we take the median value of loss aversion it is 1.82 from labour income (Treatment 1) and 1.53 from non-labour income (Treatment 2). This is consistent with our first conjecture, formalized in (2.12).

Chapman et al. (2019) use data for 2000 US respondents on MTurk to measure loss aversion using a new procedure (Dynamically optimized sequential experimental, DOSE, procedure). They find a nearly equal split between *loss averse* ($\lambda > 1$) and *loss tolerant* ($\lambda < 1$) individuals. By contrast, a comparison of 8 lab studies that allow for heterogeneity in loss aversion, as in our case, shows that loss tolerant subjects range from 13% to 30% of the total, with the rest being loss averse.[35]

[34]For instance, a simple heuristic could be to lie partially (a finding often observed in experiments). Our data is not designed to reveal the underlying reasoning behind subjects' choices, although this is an important item in the research agenda of bounded rationality. Readers interested in these issues can consult Dhami (2020, Vol. 5) and Dhami and Beinhocker (2019).

[35]These studies are Schmidt and Traub (2002); Brooks and Zank (2005); Abdellaoui et al. (2007); Abdellaoui and l'Haridon (2008); Sokol-Hessner et al., (2009); Abdellaoui et al. (2011); Sprenger (2015); Goette et al.,

Using DOSE on a sample of the student population, where they find that 10% of the subjects are loss tolerant, Chapman et al. (2019, p.3) write: "Altogether, this suggests that the prevalence of findings of loss aversion, rather than loss tolerance, may be the result of inadvertently selecting highly loss-averse samples." Thus, they appear to imply that the student population may be particularly loss averse as compared to the subject pool on MTurk. Since our subject pool is also MTurk subjects, and we use the bisection procedure that several of the 8 lab studies quoted above use, our results may be relevant for these claims. We find that 73% of our subjects in Treatment 1 and 71% in Treatment 2 are loss averse. Our estimates for the proportion of loss averse subjects are consistent with the upper end of estimates for the 8 empirical studies noted above. However, our estimates of the proporition of loss tolerant subjects (27% in T1 and 29% in T1) are much lower than the nearly 50% estimate in Chapman et al. (2019).

In our paper, there is, however, merit in following the Chapman et al. (2019) binary distinction between loss averse ($\lambda > 1$) and loss tolerant ($\lambda < 1$) subjects, but for a different reason. Many participants on MTurk are likely to be experienced professional subjects whose objectives are different from the typical student subjects in economics labs. In particular, professional subjects might participate in several online experiments during a day or week, with the objective of maximizing earnings. For many of our subjects, we find that the stated certainty equivalents of lotteries in the lottery choice task are too high. Since one of these choices is randomly picked and played for real, a professional subject whose objective is to maximize earnings, may strategically overstate the certainty equivalent. This will lead to an overestimate of their parameter of loss aversion, despite the underlying procedure being incentivized. A sensible response to this possibility is to simply separate the subjects into loss averse and loss tolerant ones, which will mitigate the effect of extreme strategic responses. For this reason, we report our main regression results with this distinction.

Chapman et al. (2019) measure risk aversion through the parameter of the power form of the utility function (this is the parameter γ in our model; see (2.10)). Whilst this is acceptable under expected utility theory, it is incorrect under prospect theory where the attitudes to risk are jointly determined by the shapes of the utility function and the probability weighting function (Dhami, 2019, Vol. 1, Sections 2.3.1, 2.4.2). Hence, the appropriate measure of risk aversion is to compare the elicited certainty equivalent and the expected value of the lottery, which is what we do (see Section 4.4). In Section 8, we show that risk aversion is an important determinant of tax evasion. We find that in Treatment 1 (labour income), 54% subjects are risk loving and 46% are risk averse. In Treatment 2 (non-labour income), 57% of the subjects are risk loving and 43% are risk averse.

7 Comparative static results for t, θ

In this section, we analyze the effect on declared income as we vary the tax rate, t, and the audit penalty rate, θ. The relevant questions are Q1-Q6, with an exogenously fixed probability of detection ($a > 0$, $b = 0$ in (2.1)); the relevant predictions are stated in Proposition 4. An

(2004).

increase in the enforcement parameter θ is predicted to reduce evasion (Proposition 4a,b) and an increase in the tax rate t is predicted to increase evasion (Proposition 4c). From Remark 2 we know that, since the results in Proposition 4 exhibit threshold effects, we may get 'stickiness' in the response of declared income to a change in the parameters.

7.1 The effect of increasing the tax rate

Table 4: Effect of increasing tax rate (two-tailed paired t-tests)

Declared income		Q1 (t=5%)	Q2 (t=30%)	Q3 (t=60%)	Q1 vs. Q2	Q1 vs. Q3	Q2 vs. Q3
Labour treatment	Mean	69.6	46.31	43.57	0.0002	0.0013	0.3817
	Median	40	20	25	(0.0009)	(0.0019)	(0.5935)
Non-labour treatment	Mean	60.2	44.61	40.84	0.0001	0.0017	0.1685
	Median	43.5	30	25	(0.0004)	(0.0028)	(0.1639)

t denotes tax rate. p-values from Wilcoxon tests are in parentheses.

Table 4 shows the average declared incomes in both treatments for Q1-Q3 ($t = 5\%, 30\%, 60\%$). We keep fixed the penalty rate ($\theta = 1$) and the audit probability ($a = 3\%$, $b = 0$). We find that the declared income goes down with an increase in the tax rate, which is consistent with our model (Proposition 4c). We also observe threshold effects. There is a significant fall in the declared income when the tax rate goes up from 5% to 30% and from 5% to 60% ($p < 0.003$ for all cases) but there is stickiness in declared income when the tax rate goes up from 30% to 60%. These results complement earlier results (see the introduction) that show an increase in evasion when the tax rate increases.

7.2 The effect of increasing deterrence parameters: audit penalty and moral costs

Table 5: Effect of increasing fine rate (two-tailed paired t-tests)

Declared income		Q4 (f=0)	Q5 (f=2)	Q6 (f=3)	Q4 vs. Q5	Q4 vs. Q6	Q5 vs. Q6
Labour treatment	Mean	39.43	43.34	60.65	0.2872	0.0007	0.0002
	Median	0	10	30	(0.043)	(0.0001)	(0.0000)
Non-labour treatment	Mean	41.33	45.06	59.41	0.2657	0.0021	0.0001
	Median	0	10	40	(0.1161)	(0.0002)	(0.0000)

f denotes fine rate. p-values from Wilcoxon tests are in parentheses.

Table 5 compares the declared income for both sources of incomes as the fine rate $f = 1 + \theta$ is varied from 0, 2, to 3 (or as the penalty rate θ is varied from -1, 1, to 2). We keep fixed the tax rate ($t = 30\%$) and the audit probability ($a = 3\%$, $b = 0$). Even when $\theta = -1$, i.e., there is an effective 100% subsidy to tax evasion, on average, 31% of the income is declared for tax purposes.[36] This is consistent with there being moral costs of tax evasion.

[36] The median of zero here arises due to the large number of taxpayers who choose to declare nothing.

In pairwise comparisons of the declared incomes for Q4, Q5, and Q6, there is a significant difference when the fine rate increases from 0 to 3 (Q4 vs Q6; p-value< 0.01). The observed positive association between the fine rate and declared income in both treatments is consistent with our theoretical prediction (Proposition 4b). However, there is no significant difference between declared incomes when the fine rate increases from 0 to 2 (Q4 vs Q5), which potentially reflects stickiness in the comparative statics (Remark 2).

8 Regression analysis of the determinants of declared income

This section gives the multinomial probit regression results for Q7 where the probability of audit increases with evaded income (as in the parametrization for audit probability given in (5.1)). The relevant predictions are summarized in Proposition 2. For Q7 we have empirically realistic values of the other policy parameters (tax rate, $t = 30\%$; penalty rate, $\theta = 2$).[37] We have already tested for the comparative static results with respect to a, θ, and t in Section 7 by inducing exogenous variation in these parameters. Except for a brief discussion towards the end of this section on tax elasticities, a, θ, and t are held fixed. We are now interested in the treatment effects, and the other determinants of tax evasion, particularly loss aversion. Recall that $Z = W - D$ denotes evaded income.

We estimate the following multinomial probit regression model.

$$P(z_1 \leq Z \leq z_2) = \Phi(\alpha_0 + \alpha_1 d_\lambda + \alpha_2 d_R + \alpha_3 d_T + \alpha_4 d_\lambda d_T + \alpha_5 d_\lambda d_R + \alpha_6 d_R d_T + \alpha_7 d_\lambda d_R d_T + \beta \mathbf{X}). \tag{8.1}$$

From Table 3 for Q7, 54% of the choices in Treatment 1 and 50% of the choices in Treatment 2 are corner solutions ($Z = 0$ or $Z = W$) , i.e., the bulk of our data is concentrated at the two extremes. Hence, we construct four categories of our dependent variable ($Z = 0$; $0 < Z < \frac{1}{2}W$; $\frac{1}{2}W \leq Z < W$; $Z = W$). In (8.1), the upper and lower limits, z_1, z_2, are used to separate the four categories of the variable Z, and Φ is the cumulative density function for a standard normal distribution. There is a roughly uniform distribution of the evasion data over the interval $0 < Z < W$, i.e., there are no spikes in this interval to suggest that another categorization of our dependent variable would be more appropriate. We have also tried Tobit models, and we briefly report the results later in this section, but there are several advantages of the multinomial probit over a Tobit analysis in our framework. First, the multinomial probit model offers a better fit to the data.[38] Second, in our model, the dependent variable in a multinomial probit is more natural, relative to the Tobit specifications.[39]

[37] By contrast, for several other questions we have extreme values of these parameters in order to induce a greater range of exogenous variation (e.g., $t = 5\%, 60\%$ and $\theta = -1, 0$). These extreme values are less empirically realistic. In Q1-Q6 we have an exogenous probability of detection. Hence, it is not appropriate to pool data for these questions with data for Q7 for regression analysis.

[38] Following the criteria suggested in Cameron and Trivedi (2010) for goodness of fit in logit models we ran a comparison of fitted and actual values which shows that multinomial probit provides a much better fit with an accuracy that is almost twice as good.

[39] In our experiments, we have 5 categories of income $W \in \{50, 100, 150, 200, 250\}$ and our predictions for each W are for the level of evasion Z, which is captured well by the LHS of the multinomial probit specification in (8.1). In particular, for the case of an endogenous detection probability, our predictions do not necessarily

The regressors listed in (8.1), and their correspondence with the names of the variables listed in Table 6, which gives the results, are as follows.

• d_λ, or 'Loss aversion' is a dummy variable that takes the value 1 if the subject is loss averse ($\lambda > 1$) and 0 if the subject is loss tolerant ($\lambda < 1$). Our reasons for using a binary measurement for loss aversion have already been discussed in Section 6.2.

• d_R, or 'Risk aversion' is a dummy variable that captures attitudes to risk. It takes the value 1 for risk averse individuals and 0 for risk loving individuals.[40]

• d_T, or 'Labor' is a treatment dummy that equals 1 for Treatment 1 (labor income) and 0 for Treatment 2 (non-labor income).

• We also have the following interaction terms between various dummy variables: $d_\lambda d_T$, $d_\lambda d_R$, $d_R d_T$, $d_\lambda d_R d_T$.

• The vector $\mathbf{X}$ contains a number of control variables that we now explain:

• 'Income' is the subject's income from the experiment. It has 5 categories, one each for the income levels 50, 100, 150, 200, 250.

• 'Time' indicates the length of time taken for the completion of the experiment.

• 'Age' gives the self-reported age of subjects.

• 'Gender' is a dummy for gender and takes values 1 for male and 0 for female.

• Marital' is a dummy for marital status and takes values 0 for single and 1 otherwise.

• 'Job' is a dummy for job status and takes values 1 for full-time job and 0 otherwise.

• 'Education' is a dummy and takes values 0 for bachelors degree or below, and 1 otherwise.

Table 6 gives our estimates for 4 different models. We focus below on the estimates from the most comprehensive model, Model 4, in Table 6; it also gives the best fit in terms of the AIC criteria and the highest log-likelihood. In order to indicate the significant variables, we rewrite the regression specification in (8.1); superscript stars indicate the significance level (*** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%; no stars denotes lack of significance).

$$P\left(z_1 \leq Z \leq z_2\right) = \Phi\left(\begin{array}{c} \alpha_0 + \alpha_1^{***} d_\lambda + \alpha_2 d_R + \alpha_3^{*} d_T + \alpha_4^{**} d_\lambda d_T + \alpha_5 d_\lambda d_R + \alpha_6^{***} d_R d_T \\ +\alpha_7^{***} d_\lambda d_R d_T + \beta \mathbf{X} \end{array}\right), \tag{8.2}$$

where the coefficients are

$$\alpha_1^{***} = -0.609; \alpha_2 = -0.365; \alpha_3^{*} = -0.457; \alpha_4^{**} = 0.598; \alpha_5 = 0.544; \alpha_6^{***} = 0.938; \alpha_7^{***} = -1.061. \tag{8.3}$$

We follow a slightly unusual notation in (8.2) and (8.3) in superscripting stars on the regression coefficients rather than on their numerical values. We find this notation more convenient for the

generalize to the case $\frac{Z}{W}$ or $\frac{D}{W}$ (see Proposition 2). By contrast, under the Tobit censored model, we need to take account of different incomes for our subjects by transforming our dependent variable to take account of of income differences, e.g., $\frac{Z}{W}$, in which case the predictions in Proposition 2 do not necessarily apply. Alternatively, we need to consider a more complex specification with levels of income on the RHS, which compromises on the degrees of freedom, as we have done in our Tobit estimates that we report below.

[40]Risk aversion is measured directly by comparing the certainty equivalent of a lottery with its expected value. As noted in Section 4.4, this variable is unrelated to loss aversion because it is measured only for lotteries in the domain of gains.

Table 6: Probit regression result when the dependent variable is evasion from Q7

Model	1	2	3	4
Loss aversion	-0.4140***	-0.6081**	-0.5843**	-0.6091***
	(0.1542)	(0.2604)	(0.2678)	(0.2236)
Risk aversion	0.0342	-0.2517	-0.2111	-0.3649
	(0.1404)	(0.4005)	(0.4142)	(0.2580)
Labour	0.0902	-0.2806	-0.3046	-0.4575*
	(0.1390)	(0.3557)	(0.3650)	(0.2654)
Loss aversion:risk aversion		0.3178	0.2365	0.5439*
		(0.4603)	(0.4835)	(0.2784)
Loss aversion:labour		0.4500	0.3844	0.5980**
		(0.4152)	(0.4268)	(0.2993)
Risk aversion:labour		0.6113	0.6088	0.9385***
		(0.5477)	(0.5659)	(0.2214)
Loss aversion:risk aversion:labour		-0.6834	-0.6432	-1.0609***
		(0.6392	(0.6626)	(0.2215)
Income1			0.2406	0.3180
			(0.2723)	(0.2943)
Income2			0.0743	0.0418
			(0.2015)	(0.1914)
Income3			-0.0906	0.0494
			(0.1760)	(0.1916)
Income4			0.4576	0.3733
			(0.3006)	(0.2961)
Time				-0.0003***
				(0.0001)
Age				0.0040
				(0.0069)
Gender				0.1467
				(0.1541)
Marital				-0.4301**
				(0.1716)
Job				0.1445
				(0.1690)
Education				-0.4775**
				(0.2174)
0—1	-0.8154***	-0.9742***	-0.9657***	-1.3403
	(0.1646)	(0.2208)	(0.2464)	(0.3666)
1—2	-0.2695*	-0.4250*	-0.4099*	-0.7584
	(0.1636)	(0.2191)	(0.2456)	(0.3671)
2—3	0.4929***	0.3398	0.3618	0.0741
	(0.1655)	(0.2201)	(0.2468)	(0.3708)
Log-Likelihood	-335.0829	-334.2649	-332.4188	-319.4756
AIC	682.1658	688.5298	692.8376	678.9513

Robust standard error in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

discussion below. The estimates are consistent with the predictions of our theoretical model, as we now explain.

Loss averse taxpayers are less likely to evade as compared to loss tolerant taxpayers as predicted in Proposition 2b (the direct effect is $\alpha_1^{***} = -0.609$). To the best of our knowledge, this is the first demonstration of the link between loss aversion and evasion, first formally shown in Dhami and al-Nowaihi (2007), that is based on a "direct" individual-level measurement of loss aversion. We give a more nuanced discussion of the effects of loss aversion below that takes account of interaction terms.

As noted in Section 3.3 and Remark 3, loss aversion and moral costs of evasion work in opposite directions: Loss aversion induces taxpayers to evade less in Treatment 1 (labor income) and moral costs induce the tax evader to evade more in Treatment 1. From Section 7.2 we know that moral costs of tax evasion are important in our data. Average declared income is about 31%, even when there is a 100% subsidy to tax evasion (and this figure is likely to be non-zero for much lower subsidies). As noted earlier, the median value of loss aversion is 1.82 from labour income (Treatment 1) and 1.53 from non-labour income (Treatment 2) and loss aversion directly reduces the probability of evasion ($\alpha_1^{***} = -0.609$). The direct treatment effect ($\alpha_3^{*} = -0.457$) shows that the probability of evasion is relatively lower in Treatment 1 (labour income), albeit only weakly significant at 10%. Hence, the overall negative treatment effect is consistent with the inference that loss aversion is a relatively stronger influence on evasion as compared to moral costs. This can, of course, also imply that there are no moral costs of evasion at all and that our data can be explained by loss aversion alone. However, given the experimental evidence discussed in the introduction, we believe that it is difficult to separate moral costs from illegal activity.

Several interaction terms, $\alpha_3^{*}, \alpha_4^{**}, \alpha_6^{***}, \alpha_7^{***}$, that involve the treatment dummy d_T, are statistically significant. In the absence of mental accounting, none of these coefficients should be significantly different from zero. Yet these terms have the expected economic interpretation when one invokes mental accounting and, thus, they provide evidence for mental accounting. Furthermore, the role of loss aversion, through the coefficients, $\alpha_1^{***}, \alpha_4^{**}, \alpha_7^{***}$, provides support for our transmission mechanism. We now discuss these issues. In particular, the separate, and intertwined, effects of loss aversion and risk aversion, which have been ignored in the tax evasion literature, turn out to be fairly subtle. Consider the following two potentially surprising effects that may, at first sight, appear counterintuitive.

(1) An increase in risk aversion directly reduces evasion, $\alpha_2 = -0.365$, although the effect is not significant. However, the interaction of risk aversion with the treatment dummy ($\alpha_6^{***} = 0.938$) shows that relative to risk loving taxpayers, risk averse taxpayers evade more tax in Treatment 1.

(2) Loss averse individuals evade significantly lower tax ($\alpha_1^{***} = -0.609$). However, the interaction of loss aversion and the treatment dummy is significantly positive ($\alpha_4^{**} = 0.598$), i.e., loss averse individuals would appear to evade more in Treatment T1.

Both these effects are driven mainly by the loss tolerant individuals. If we consider the three way interaction, $d_\lambda d_R d_T$, then the relevant regression parameter ($\alpha_7^{***} = -1.061$) shows that loss averse individuals who are risk averse and in Treatment 1, actually evade significantly lower tax, which is consistent with our predictions. To see this more formally, let us focus on risk averse subjects, i.e., $d_R = 1$, and consider all possible pairs of combinations of $(d_\lambda, d_T) \in \{(0,0), (0,1), (1,0), (1,1)\}$. Using (8.2) we can compute the following conditional probabilities.

$$P(z_1 \leq Z \leq z_2 \mid d_\lambda = 0, d_T = 0) = \Phi(\alpha_0 + \alpha_2 + \beta\mathbf{X}) \tag{8.4}$$

$$P(z_1 \leq Z \leq z_2 \mid d_\lambda = 1, d_T = 0) = \Phi(\alpha_0 + \alpha_2 + \alpha_1^{***} + \alpha_5 + \beta\mathbf{X}) \tag{8.5}$$

$$P(z_1 \leq Z \leq z_2 \mid d_\lambda = 0, d_T = 1) = \Phi(\alpha_0 + \alpha_2 + \alpha_3^{*} + \alpha_6^{***} + \beta\mathbf{X}) \tag{8.6}$$

$$P(z_1 \leq Z \leq z_2 \mid d_\lambda = 1, d_T = 1) = \Phi(\alpha_0 + \alpha_2 + \alpha_3^{*} + \alpha_6^{***} + \alpha_1^{***} + \alpha_4^{**} + \alpha_5 + \alpha_7^{***} + \beta\mathbf{X}) \tag{8.7}$$

In (8.4), (8.5), we consider non-labor income, i.e., Treatment 2 ($d_T = 0$) and we vary individuals from loss tolerant ($d_\lambda = 0$) to loss averse ($d_\lambda = 1$). The marginal effect is 'reflected' in the difference in the intercept, given by $\alpha_1^{***} + \alpha_5 = -0.065$ (or -0.609 if we omit the insignificant coefficient α_5).[41] Thus, relative to loss tolerant subjects, loss averse taxpayers evade lower taxes in Treatment 2, which is consistent with our prediction in Proposition 2b. Comparing (8.6), (8.7) we can compute a similar marginal effect for labour income, i.e., Treatment 1 ($d_T = 1$). The marginal effect in this case is 'reflected' in the sum of coefficients $\alpha_1^{***} + \alpha_4^{**} + \alpha_5 + \alpha_7^{***} = -0.528$ (or -1.072 if we omit the insignificant coefficient α_5), which shows that, relative to loss tolerant subjects, loss averse individuals in treatment T1 evade lower tax (as predicted in Proposition 2b). In particular, the marginal impact is about 8 times larger in T1 relative to T2 (or about 1.75 times as large if we omit α_5). This also supports our assertion about the differential effects of loss aversion depending on the source of the income, and further establishes the relevance of mental accounting.

We can also express the significance of the interaction terms in terms of *intercept effects* and *slope effects*. The intercept effect is independent of the explanatory variables, and the slope effect captures the marginal effectiveness of loss aversion, relative to loss tolerance, as captured through the loss aversion dummy, d_λ, in explaining tax evasion. Taking conditional expectations on both sides of (8.2) for all possible pairs of combinations of $(d_R, d_T) \in \{(0,0), (0,1), (1,0), (1,1)\}$ we get:

$$P(z_1 \leq Z \leq z_2 \mid d_R = 0, d_T = 0) = \Phi(\alpha_0 + \alpha_1^{***} d_\lambda + \beta\mathbf{X}). \tag{8.8}$$

$$P(z_1 \leq Z \leq z_2 \mid d_R = 1, d_T = 0) = \Phi(\alpha_0 + \alpha_2 + (\alpha_1^{***} + \alpha_5) d_\lambda + \beta\mathbf{X}). \tag{8.9}$$

$$P(z_1 \leq Z \leq z_2 \mid d_R = 0, d_T = 1) = \Phi(\alpha_0 + \alpha_3^{*} + (\alpha_1^{***} + \alpha_4^{**}) d_\lambda + \beta\mathbf{X}). \tag{8.10}$$

$$P(z_1 \leq Z \leq z_2 \mid d_R = 1, d_T = 1) = \Phi\left(\begin{array}{c} \alpha_0 + \alpha_2 + \alpha_3^{*} + \alpha_6^{***} \\ +(\alpha_1^{***} + \alpha_4^{**} + \alpha_5 + \alpha_7^{***}) d_\lambda + \beta\mathbf{X} \end{array}\right). \tag{8.11}$$

Begin with the case $(d_R, d_T) = (0,0)$ in (8.8), where the taxpayer is risk loving ($d_R = 0$) and is in Treatment 2 ($d_T = 0$). Now move to the case $(d_R, d_T) = (1,0)$ in (8.9) which denotes a risk averse taxpayer ($d_R = 1$) who continues to be in Treatment 2. Neither the intercept effect

[41] We use the term 'reflected' because to find the exact marginal effect, one needs to compute the changes in the cumulative distribution function Φ.

($\alpha_2 = -0.365$) nor the slope effect ($\alpha_5 = 0.544$) is significantly different from zero in this case. Now consider equations (8.10), (8.11), which offer a similar comparison, but for Treatment 1 ($d_T = 1$). Here, the intercept effect is $\alpha_2 + \alpha_6^{***}$ and the slope effect is $\alpha_5 + \alpha_7^{***}$. Restricting attention to the coefficients significantly different from zero, we get the intercept effect as $\alpha_6^{***} = 0.938$ and the slope effect as $\alpha_7^{***} = -1.061$. The slope effect shows that the marginal effect of being loss averse ($d_\lambda = 1$) in Treatment 1 increases for risk averse taxpayers relative to risk loving taxpayers. Furthermore, this effect is to reduce evasion. This also highlights the differing roles for loss aversion for each source of income, which supports our assertion of mental accounting.

Married taxpayers and more educated taxpayers are likely to evade less (see Table 6). There is some evidence in the literature that married people engage in less social security cheating (LaLumia and Sallee, 2013).

We now give a brief summary of the results from the other regressions that we ran. When we average evasion across all the 7 questions, instead of just Q7, the results are as follows. Loss aversion continues to be a significant determinant of tax evasion with the correct sign. The coefficient of risk aversion is insignificant. The marginal treatment effect is negative (greater evasion in Treatment 1). The three way interaction term ($d_\lambda d_R d_T$) is significant and negative. Males are more likely to evade taxes than females. As compared to single people, married people or people with experience of living with a partner are less likely to evade taxes.

We also ran individual regressions corresponding to the evasion decision for each of the first 6 questions. These results are also similar. The coefficient of loss aversion is negative and significant in 4 out of 6 cases. The coefficient of risk aversion is insignificant in 6 cases, and in the one exception where it is significant, it is negative (more risk averse individuals evade less). The three way interaction term ($d_\lambda d_R d_T$) is significant and negative in all cases. The marginal treatment effects, corresponding to the variable d_T, are mostly insignificant. However, due to the interaction term, there are significant slope effects.

Our reasons for preferring the multinomial probit to censored Tobit have been outlined above. Following Alm et al. (1992), we also used a Tobit model to estimate determinants of compliance and to estimate elasticities of "declared income" with respect to several variables. We can estimate elasticities by exploiting the (i) variation in the tax rate and the audit penalty in Q1-Q6 of our experiment, and (ii) variation in the income levels. Loss aversion remains a significant determinant of reported income. When computing elasticities at the mean values of the variables, our results are consistent with other empirical work; see Alm (1992, 2019). In particular, higher tax rates lead to lower reported income. The tax rate elasticity of declared income is equal to -0.3126. Moreover, higher income leads to higher compliance and the income elasticity is significant and positive, 1.02. We also find a fine rate elasticity of declared income of 0.5040, which is positive and significant.

9 Conclusions

Mental accounting, originating in the work of Richard Thaler, likely played a key role in the determination of the 2017 Nobel Prize in economics. Our work is one of the first applications of this idea to tax evasion that uses a rigorous theoretical model, followed by stringent empirical testing of the predictions. Our general methods should have wider applicability.

There are several novel features of our analysis. First, we provide a theoretical analysis of the link between loss aversion and mental accounting, then we propose a measure of loss aversion, followed by the "direct" elicitation of loss aversion for each subject using the bisection method. We are also able to accurately measure risk aversion by comparing the certainty equivalent of a lottery with its expected value. Second, our empirical results show that loss aversion, and a combination of loss aversion and risk aversion, are essential for an understanding of tax evasion that depends on the source of income. Our paper is possibly the first to empirically explore the interaction between these two measures. Third, we confirm the predicted comparative static effects of the probability of detection, and the tax rate on tax evasion for the same set of subjects, for two different sources of income. In particular, we show that when there is an effective subsidy of 100% on evaded taxes, on average, taxpayers still declared 31% of their income. This suggests that moral costs of evasion play an important role in the evasion decision, which dovetails nicely with other evidence from behavioral economics. Fourth, loss aversion appears to be a stronger influence than moral costs of evasion in explaining tax evasion.

Our modelling of mental accounting is likely to spur further applications in economics. The inescapable constraints caused by the Covid19 situation led us to conduct online experiments using MTurk. It will be useful to replicate our results with tightly controlled lab experiments, at a time when such experiments are possible. We do not anticipate that our main results will change. It is likely that the student subject pool with tighter experimental controls will permit our methods to obtain an even more accurate measure of loss aversion and risk aversion.

We also make some suggestions for future research. The interaction effects between loss aversion and risk aversion in our empirical results may result in the construction of a richer theoretical model with even better explanatory power. One may wish to estimate the parameters of the probability weighting function that will allow us to map our measured risk attitudes into measures of optimism and pessimism (Wakker, 2010; Section 6.3; Dhami, 2019, Vol. 1, Sections 2.3.1, 2.4.2); this may offer an improved ability to explain tax evasion. Our approach is static. Future work can introduce dynamics, for instance, the dynamic taxation of consumption and savings, when they arise from different sources. Another fruitful approach may arise from incorporating mental accounting into the determination of optimal income taxation of different sources of incomes and may have insights for the debate between income and consumption taxes.

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References

[1] Abdellaoui, M. (2000). Parameter-Free Elicitation of Utility and Probability Weighting Functions. Management Science 46(11): 1497-1512.

[2] Abdellaoui, M., Bleichrodt, H., and Paraschiv, C. (2007). Loss Aversion under Prospect Theory: A Parameter-Free Measurement. Management Science 53(10): 1659-1674.

[3] Abdellaoui, M. and l'Haridon, O. (2008). A Tractable Method to Measure Utility and Loss Aversion under Prospect Theory. Journal of Risk and Uncertainty 36(3): 245-266.

[4] Abdellaoui, M., L'Haridon, O., and Paraschiv, C. (2011). Experienced vs. Described Uncertainty: Do We Need Two Prospect Theory Specifications? Management Science 57(10): 1879-1895.

[5] al-Nowaihi, A., Bradley, I., and Dhami, S. (2008). A note on the utility function under prospect theory. Economics Letters. 99(2): 337–339.

[6] al-Nowaihi, A., Dhami, S., 2006. A simple derivation of Prelec's probability weighting function. Journal of Mathematical Psychology 50(6): 521-524.

[7] Allingham, M.G., Sandmo, A., 1972. Income tax evasion: a theoretical analysis. Journal of Public Economics 1(3-4): 323-238.

[8] Alm, J. (2019) What Motivates Tax Compliance. Journal of Economic Surveys. 33(2): 353-388.

[9] Alm, J., and Torgler, B. (2012). Do ethics matter? Tax compliance and morality. Journal of Business Ethics 101(4): 635-651.

[10] Alm, J., Jackson, B. R. and McKee, M. (1992). Estimating the determinants of taxpayer compliance with experimental data. National Tax Journal 45(1): 107-114.

[11] Andreoni, J., Erard, B, and Feinstein, J. (1998). Tax Compliance. Journal of Economic Literature 36(2): 818-860.

[12] Battigalli, P. and Dufwenberg, M. (2007). Guilt in games. American Economic Review 97(2): 170–6.

[13] Bernasconi, M., 1998. Tax evasion and orders of risk aversion. Journal of Public Economics 67(1), 123-134.

[14] Bernasconi, M., Zanardi, A. (2004). Tax evasion, tax rates and reference dependence. FinanzArchiv 60(3), 422-445.

[15] Brooks, P. and Zank, H. (2005). Loss Averse Behavior, Journal of Risk and Uncertainty 31(3): 301-325.

[16] Bruhin, A., Fehr-Duda, H., and Epper, T. (2010). Risk and rationality: uncovering heterogeneity in probability distortion. Econometrica 78(4): 1375–412.

[17] Bénabou, R., and Tirole, J. (2002). Self-Confidence and Personal Motivation. The Quarterly Journal of Economics 117(3): 871–915.

[18] Bénabou, R. and Tirole, J. (2003). Intrinsic and extrinsic motivation. Review of Economic Studies 70(3): 529–44.

[19] Bicchieri, C. (2006). The Grammar of society: The nature and dynamics of social norms. New York: Cambridge University Press.

[20] Cameron, A. C., and Trivedi, P. K. (2010) Microeconometrics Using Stata. Revised Edition. College Station, Texas: Stata Press.

[21] Cappelen, A. W., Hole, A. D., Sørensen, E. Ø. and Tungodden, B. (2007). The pluralism of fairness ideals: An experimental approach. American Economic Review 97(3): 818–827.

[22] Chambers, V., and Spencer, M. (2008). Does Changing the Timing of a Yearly Individual Tax Refund Change the Amount Spent vs. Saved? Journal of Economic Psychology 29(6):856–62.

[23] Chapman, J., Snowberg, E., Wang, S., and Camerer, C. (2019) Loss Attitudes in the U.S. Population: Evidence from Dynamically Optimized Sequential Experimentation (DOSE). Mimeo Princeton University.

[24] Cherry, T.L., Frykblom, P., and Shogren, J.F. (2002). Hardnose the dictator. American Economic Review. 92(4): 1218–1221.

[25] Clotfelter, C.T., (1983). Tax evasion and tax rates: an analysis of individual returns. Review of Economics and Statistics 65(3): 363-373.

[26] Crawford, V. P. and Meng, J. (2011). New York City cab drivers' labor supply revisited: reference-dependent preferences with rational-expectations targets for hours and income. American Economic Review 101(5): 1912–32.

[27] Dhami, S. (2019) Foundations of behavioral economic analysis: Volume I: Behavioral Decision Theory. Oxford University Press: Oxford.

[28] Dhami, S. (2019) Foundations of behavioral economic analysis: Volume II: Other-Regarding preferences. Oxford University Press: Oxford.

[29] Dhami, S. (2020) Foundations of behavioral economic analysis: Volume V: Bounded Rationality. Oxford University Press: Oxford.

[30] Dhami, S. (2020) Foundations of behavioral economic analysis: Volume VII: Further Topics in Behavioral Economics. Oxford University Press: Oxford.

[31] Dhami, S. and Beinhocker, E. (2019). The Behavioral Foundations of New Economic Thinking. Available at SSRN: https://ssrn.com/abstract=3454822 or http://dx.doi.org/10.2139/ssrn.3454822.

[32] Dhami, S., and al-Nowaihi. (2007). Why do people pay taxes: Expected utility versus prospect theory, Journal of Economic Behaviour and Organization 64(1): 171–192.

[33] Dhami, S., and al-Nowaihi. (2010). Optimal income taxation in the presence of tax evasion: Expected utility versus prospect theory, with Ali al-Nowaihi. Journal of Economic Behavior and Organization, 75(2): 313-337.

[34] Dhami, S., Manifold, E., and al-Nowaihi. (2020). Identity and Redistribution: Theory and Evidence. Forthcoming in Economica.

[35] Eide, E., von Simson, K., and Strom, S. (2011). Rank-dependent utility, tax evasion, and labor supply. FinanzArchiv 67(3): 261-281.

[36] Elster, J. (2011). Norms, in P. Bearman and P. Hedström, eds., The Oxford Handbook of Analytical Sociology. Oxford University Press, Oxford, UK, pp. 195–217.

[37] Engström, P., Nordblom, K., Ohlsson, H., and Persson, A. (2015). Tax Compliance and Loss Aversion. American Economic Journal: Economic Policy, 7(4): 132-64.

[38] Erard, B., and Feinstein, J. S. (1994). The role of moral sentiments and audit perceptions in tax compliance. Public Finance 49(1): 70-89.

[39] Fehr, E., Götte, L. (2007). Do workers work more if wages are high? Evidence from a randomized field experiment. America Economic Review 97(1), 298–317.

[40] Feinstein, J. S. (1991). An econometric analysis of income tax evasion and its detection. RAND Journal of Economics 22, 14-35.

[41] Fochman, M. and Wolf, N. (2015) Mental accounting in tax evasion decisions: An experiment on underreporting and overdeducting. Arqus Discussion Papers in Quantitative Tax Research No 186.

[42] Friedland, N., Maital, S., Rutenberg, A. (1978). A simulation study of income tax evasion. Journal of Public Economics 10(1), 107-116.

[43] Giamattei, M., Yahosseini, K. S., Gächter, S. and Molleman, L. (2020). LIONESS Lab: a free web-based platform for conducting interactive experiments online. Journal of the Economic Science Association JESA . https://doi.org/10.1007/s40881-020-00087-0.

[44] Goette, L., Huffman, D., and Fehr, E. (2004). Loss Aversion and Labor Supply. Journal of the European Economic Association 2(2-3): 216-228.

[45] Gordon, J. P. F. (1989). Individual morality and reputation costs as deterrents to tax evasion. European Economic Review 33(4), 797-805.

[46] Hoffman, E., and Spitzer, M.L. (1982). The Coase theorem: some experimental tests. Journal of Law and Economics. 25(1): 73–98.

[47] Jackson, S. B., Shoemaker, P. A., Barrick, J. A. and Greg, B. F. (2005). Taxpayers' Prepayment Positions and Tax Return Preparation Fees. Contemporary Accounting Research 22: 409–47.

[48] Kahneman, D., and Tversky, A. (1984). Choices, Values, and Frames. American Psychologist 39(4): 341–50.

[49] Kahneman, D., Tversky, A. (Eds.). (2000). Choices, values and frames. Cambridge: Cambridge University Press.

[50] Kahneman, D., Tversky, A. (1979). Prospect theory: an analysis of decision under risk. Econometrica 47(2): 263-291.

[51] LaLumia, S., and Sallee, J. M. (2013). The Value of Honesty: Empirical Estimates from the Case of the Missing Children. International Tax and Public Finance 20(2): 192-224.

[52] Lee, K. and Shahriar, Q. (2017). Fairness, One's Source of Income, and Others' Decisions: An Ultimatum Game Experiment. Managerial and Decision Economics 38(3): 423-431.

[53] Levitt, S. D., and List, J. A. (2007). What Do Laboratory Experiments Measuring Social Preferences Reveal About the Real World? Journal of Economic Perspectives 21(2): 153-174.

[54] List, J.A., and Cherry, T.L. (2000). Learning to accept in ultimatum games: evidence from an experimental design that generates low offers. Experimental Economics. 3(1):11–29.

[55] Locke, E. A. and Latham, G. P. (1990). A Theory of Goal Setting and Task Performance. Englewood Cliffs, NJ: Prentice-Hall.

[56] Muehlbacher, S., and Kirchler, E. (2013). Mental Accounting of Self employed Taxpayers: On the Mental Segregation of the Net Income and the Tax Due. FinanzArchiv: Public Finance Analysis 69(4):412–38.

[57] Muehlbacher, S., Hartl, B. and Kirchler, E. (2017). Mental accounting and tax compliance: Experimental evidence for the effect of mental segregation of tax due and revenue on compliance. Public Finance Review 45(1): 118-139.

[58] Olsen, J., Kasper, M., Kogler, C., Muehlbacher, S., and Kirchler, E. (2019). Mental accounting of income tax and value added tax among self-employed business owners. Journal of Economic Psychology 70(C): 125-139.

[59] Oxoby, R., and Spraggon, J. (2008) Mine and Yours: Property rights in dictator games. Journal of Economic Behavior and Organization 65(3-4):703-713.

[60] Prelec, D. and Loewenstein, G. (1998). The red and the black: mental accounting of savings and debt. Marketing Science 17(1): 4–28.

[61] Prelec, D. (1998). The probability weighting function. Econometrica 66(3), 497-528.

[62] Pudney, S., Pyle, D. and Saruc, T. (2000) Income tax evasion: An experimental approach. In MacDonald, A. and Pyle, D. Illicit activity: The economics of crime and tax fraud (Ashgate:Aldershot).

[63] Robinson, J., Rosenzweig, C., Moss, A. J., & Litman, L. (2019). Tapped out or barely tapped? Recommendations for how to harness the vast and largely unused potential of the Mechanical Turk participant pool. PloS one 14(12), e0226394. https://doi.org/10.1371/journal.pone.0226394.

[64] Rees-Jones, A. (2018). Quantifying Loss-Averse Tax Manipulation. The Review of Economic Studies 85(2):1251–1278.

[65] Sauter, M., Draschkow, D., & Mack, W. (2020). Building, Hosting and Recruiting: A Brief Introduction to Running Behavioral Experiments Online. Brain sciences, 10(4): 251. https://doi.org/10.3390/brainsci10040251.

[66] Schmidt, U., and Traub, S. (2002). An Experimental Test of Loss Aversion. Journal of Risk and Uncertainty 25(3): 233-249.

[67] Skinner, J., Slemrod, J. (1985). An economic perspective on tax evasion. National Tax Journal 38, 345-353.

[68] Slemrod, J. (2018). Tax compliance and enforcement. National Bureau of Economic Research. Working Paper No. 24799.

[69] Slemrod, J., and Yitzhaki, S., (2002). Tax avoidance, evasion and administration. In: Auerbach, A.J., Feldstein, M. (Eds.). Handbook of Public Economics, Vol. 3. Amsterdam: Elsevier Science, chapter 22, 1423-1470.

[70] Sokol-Hessner, P., Hsu, M., Curley, N. G., Delgado, M. R., Camerer, C. F., and Phelps, E. A. (2009). Thinking Like a Trader Selectively Reduces Individuals' Loss Aversion. Proceedings of the National Academy of Sciences 106(13): 5035-5040.

[71] Soman, D. and Cheema, A. (2004). When goals are counter-productive: the effects of violation of a behavioral goal on subsequent performance. Journal of Consumer Research 31(1): 52–62.

[72] Sprenger, C. (2015). An Endowment E ect for Risk: Experimental Tests of Stochastic Reference Points. Journal of Political Economy 123(6): 1456-1499.

[73] Thaler, R. (1985). Mental accounting and consumer choice. Marketing Science 4: 199–214. Republished (2008) in Marketing Science 27(1): 15–25.

[74] Thaler, R. and Johnson, E. (1990). Gambling with the house money and trying to break even: the effects of prior outcomes on risky choice. Management Science 36(6): 643–60.

[75] Thaler, R. H. (1999). Mental accounting matters. Journal of Behavioral Decision Making 12(3): 183–206.

[76] Tversky, A., Kahneman, D., (1992). Advances in prospect theory: cumulative representation of uncertainty. Journal of Risk and Uncertainty 5(4): 297-323.

[77] Yaniv, G. (1999). Tax compliance and advance tax payments: a prospect theory analysis. National Tax Journal 52(4): 753-764.

[78] Yitzhaki, S. (1974). A note on income tax evasion: a theoretical analysis. Journal of Public Economics 3(2): 201-202.

[79] Yoder, K. J., and Decety, J. (2018). The neuroscience of morality and social decision-making. Psychology, Crime and Law 24(3): 279–295. https://doi.org/10.1080/1068316X.2017.1414817.

10 Appendix: Proofs

Proof of Lemma 1: For any reference point R, we get

$$X^{NC} = W - tD - c\,(W - D) - R,\ 0 \leq D \leq W. \tag{10.1}$$

$$X^{C} = (1 - t)\,W - (\theta t + c)\,(W - D) - R,\ 0 \leq D \leq W. \tag{10.2}$$

For the taxpayer always to be in the domain of gains if not caught, we must have

$$X^{NC} \geq 0 \text{ for all } D \in [0, W]\,. \tag{10.3}$$

Similarly, for the taxpayer always to be in the domain of losses if caught, we must have

$$X^{C} \leq 0 \text{ for all } D \in [0, W]\,. \tag{10.4}$$

Note that (10.1)-(10.4), must hold for any $D \in [0, W]$; hence, we get that the reference point must satisfy

$$R \in [(1 - t)\,W - (\theta t + c)\,(W - D)\,, W - tD - c\,(W - D)] \equiv [l_1, l_2]\,. \tag{10.5}$$

where l_1 and l_2 are, respectively, the lower and upper limits of the interval. Notice that $\frac{dl_1}{dD} = (\theta t + c) > 0$ and $\frac{dl_2}{dD} = -t + c < 0$ (because, from (2.3), $t > c$). Hence, as one moves from $D = 0$ to $D = W$ one gets nested intervals within which R must lie. Since $D \in [0, W]$ we need only check the case $D = W$ to ensure that the reference point holds for all possible values of D.

In particular, for $D = W$, (10.1) and (10.3) give

$$R \leq (1-t)\,W. \tag{10.6}$$

Similarly, for $D = W$, (10.2) and (10.4) give

$$R \geq (1-t)\,W. \tag{10.7}$$

From (10.6) and (10.7) we get $R = (1-t)\,W$ as the unique reference point. ■

Proof of Proposition 1: (a) Since $V(D,\phi)$ is a twice continuously differentiable function of D on the non-empty compact interval $[0,W]$, it attains a maximum at some point $D^* \in [0,W]$.

(b) Let us rewrite $V(D,\phi)$ in (3.1) as

$$V(D,\phi) = (W-D)^{\gamma}\left[(t-c)^{\gamma} - Ap\,(D)\right], \tag{10.8}$$

where

$$A = \left[(t-c)^{\gamma} + \lambda\,(\theta t + c)^{\gamma}\right] > 0. \tag{10.9}$$

If the optimal choice $D^* = W$, then from the objective function in (3.1), $V(W,\phi) = 0$. Hence, if there is an interior solution $D^* \in (0,W)$ it must be that $V(D^*,\phi) \geq 0$. It follows from (10.8) and (10.9) that for $D^* \in (0,W)$.

$$(t-c)^{\gamma} - Ap\,(D) \geq 0. \tag{10.10}$$

We can write (3.2) as

$$\frac{\partial V}{\partial D} = -\left[(t-c)^{\gamma} - Ap\,(D)\right]\gamma\,(W-D)^{\gamma-1} + (W-D)^{\gamma}\,bA. \tag{10.11}$$

At an interior solution $\frac{\partial V}{\partial D} = 0$. Using (10.11) this implies that

$$bA = \left[(t-c)^{\gamma} - Ap\,(D)\right]\gamma\,(W-D)^{-1}. \tag{10.12}$$

Differentiating $\frac{\partial V}{\partial D}$ with respect to D, and substituting bA from (10.12), we get

$$\frac{\partial^2 V}{\partial D^2} = -\gamma bA\,(W-D)^{\gamma-1} - \gamma\,(W-D)^{\gamma-2}\left[(t-c)^{\gamma} - Ap\,(D)\right]. \tag{10.13}$$

From (10.10), we have $(t-c)^{\gamma} - Ap\,(D) \geq 0$, hence, $\frac{\partial^2 V}{\partial D^2} < 0$, which gives uniqueness of the interior solution.

Since $\frac{\partial^2 V}{\partial D^2} \neq 0$, D^* is a regular point of $\frac{\partial V}{\partial D}$. Using the implicit function theorem, for any $D^* \in (0,W)$,

$$\frac{\partial D^*}{\partial z} = -\frac{\partial^2 V}{\partial D \partial z} \Big/ \frac{\partial^2 V}{\partial D^2};\ z = \theta, t, a, b, \gamma, c, \lambda. \tag{10.14}$$

Since $\frac{\partial^2 V}{\partial D^2} < 0$, it follows that the sign of $\frac{\partial D^*}{\partial z}$ is that of $\frac{\partial^2 V}{\partial D \partial z}$. ■

Proof of Proposition 2: Using Proposition 1(b), we now sequentially determine the signs of the derivatives in (10.14).

(a) Implicitly differentiating the first order condition (3.2), we get

$$\frac{\partial^2 V}{\partial D \partial \theta} = \lambda\gamma t\,(\theta t + c)^{\gamma-1}\left[p\,(D)\,\gamma\,(W-D)^{\gamma-1} + b\,(W-D)^{\gamma}\right] > 0. \tag{10.15}$$

Using Proposition 1b and (10.15), we get that $\frac{\partial D^*}{\partial \theta} > 0$.

The probability of detection is given by $p(D) = a - bD$, where a is the exogenous probability of detection. Implicitly differentiating the first order condition (3.2), we get

$$\frac{\partial^2 V}{\partial D \partial a} = \gamma (W - D)^{\gamma - 1} [(t - c)^\gamma + \lambda (\theta t + c)^\gamma] > 0. \tag{10.16}$$

Using Proposition 1b and (10.16), we get that $\frac{\partial D^*}{\partial a} > 0$.

(b) Comparative static effects of loss aversion, λ.

Implicitly differentiating the first order condition (3.2)

$$\frac{\partial^2 V}{\partial D \partial \lambda} = -(\theta t + c)^\gamma \left[-p(D) \gamma (W - D)^{\gamma - 1} - b (W - D)^\gamma \right] > 0. \tag{10.17}$$

Using Proposition 1b, and (10.17), it follows that $\frac{\partial D^*}{\partial \lambda} > 0$.

(c) Comparative static effects of the tax rate, t.

Implicitly differentiating the first order condition (3.2), we get

$$\begin{aligned} \frac{\partial^2 V}{\partial D \partial t} &= \gamma (t - c)^{\gamma - 1} \left[-(1 - p(D)) \gamma (W - D)^{\gamma - 1} + b (W - D)^\gamma \right] \\ &\quad -\lambda \gamma \theta (\theta t + c)^{\gamma - 1} \left[-p(D) \gamma (W - D)^{\gamma - 1} - b (W - D)^\gamma \right]. \end{aligned} \tag{10.18}$$

Define

$$P = p(D) \gamma (W - D)^{\gamma - 1} + b (W - D)^\gamma > 0. \tag{10.19}$$

Using (10.19), the first order condition for an interior optimum, $\frac{\partial V}{\partial D} = 0$ in (3.2), can the be written as

$$(t - c)^\gamma \left[-\gamma (W - D)^{\gamma - 1} + P \right] = -P \lambda (\theta t + c)^\gamma . \tag{10.20}$$

Using (10.19), (10.18) can be rewritten as

$$\frac{\partial^2 V}{\partial D \partial t} = \gamma (t - c)^{\gamma - 1} \left[-\gamma (W - D)^{\gamma - 1} + P \right] + P \lambda \gamma \theta (\theta t + c)^{\gamma - 1} . \tag{10.21}$$

Substitute (10.20) in (10.21)

$$\frac{\partial^2 V}{\partial D \partial t} = -c (1 + \theta) \frac{P \gamma \lambda (\theta t + c)^\gamma}{(t - c)(\theta t + c)} < 0. \tag{10.22}$$

It follows from Proposition 1b, (10.19), and (10.22) that $\frac{\partial D^*}{\partial t} < 0$.

(d) Comparative static effects of morality costs, c.

The first order condition (3.2) for an interior optimum can be written as:

$$\frac{\partial V}{\partial D} = (t - c)^\gamma Z_1 + \lambda (\theta t + c)^\gamma Z_2 = 0 \tag{10.23}$$

where $Z_1 = \left[-(1 - p(D)) \gamma (W - D)^{\gamma - 1} + b (W - D)^\gamma \right]$ and $Z_2 = \left[p(D) \gamma (W - D)^{\gamma - 1} + b (W - D)^\gamma \right] > 0$ are independent of c. Z_2 is positive, therefore, an interior solution requires that $Z_1 < 0$ (by assumption, $t \geq c$). It follows that

$$\frac{\partial^2 V}{\partial D \partial c} = -\gamma (t - c)^{\gamma - 1} Z_1 + \lambda \gamma (\theta t + c)^{\gamma - 1} Z_2 > 0. \tag{10.24}$$

Using Proposition 1b and (10.24), we have that $\frac{\partial D^*}{\partial c} > 0$. ■

Proof of Proposition 3: (a) Evaluating $\frac{\partial V}{\partial D}$ in (10.11) at $D = 0$ we get

$$\frac{\partial V}{\partial D} \mid_{D=0} = W^{\gamma} \left[- \left[(t-c)^{\gamma} - Aa \right] \gamma W^{-1} + bA \right],$$

where $A = \left[(t-c)^{\gamma} + \lambda \left(\theta t + c \right)^{\gamma} \right] > 0$ is defined in (10.9). It follows that $\frac{\partial V}{\partial D} \mid_{D=0} < 0$ if

$$a < \widehat{a} = \left(1 + \frac{\lambda \left(\theta t + c \right)^{\gamma}}{(t-c)^{\gamma}} \right)^{-1} - \frac{1}{\gamma} bW$$

Then, for $D \in [0, W)$, $D^* = 0$ is optimal if $\widehat{a} > 0$ and $a < \widehat{a}$.

(b) Suppose D^* is on the lower boundary (i.e., $D^* = 0$). Then, at $D = D^* = 0$, $\frac{\partial V}{\partial D} \leq 0$. A few simple calculations show that $\frac{\partial^2 V}{\partial D \partial t} < 0$. Since $\frac{\partial V}{\partial D} \leq 0$, an increase in t will make $\frac{\partial V}{\partial D}$ strictly negative. Thus, an increase in D would reduce utility. Hence, D^* cannot increase as a result of an increase in t. A similar argument shows that D^* is non-decreasing function of each of a, b, c, θ, and λ.

Suppose D^* is on the upper boundary (i.e., $D^* = W$). Then, at $D = D^* = W$, $\frac{\partial V}{\partial D} \geq 0$. An argument similar to (b) shows that D^* cannot increase as a result of an increase in a, b, c, θ, and λ. Since $\frac{\partial^2 V}{\partial D \partial t} < 0$ at $D^* = W$, but $\frac{\partial V}{\partial D} \geq 0$ so D^* is non-decreasing function of t. ■

Proof of Proposition 4: From (3.4), we have that $h(\phi) = (t-c)^{\gamma} \left[(1-a) - a\lambda \left(\frac{\theta t + c}{t-c} \right)^{\gamma} \right]$.

(a) (Exogenous probability of detection, a) h is a continuous function of a on the compact set $[0, 1]$. We have $\frac{\partial h}{\partial a} = -(t-c)^{\gamma} - \lambda \left(\theta t + c \right)^{\gamma} < 0$. Furthermore: (i) $h \mid_{a=0} = (t-c)^{\gamma} > 0$, and (ii) $h \mid_{a=1} = -\lambda \left(\theta t + c \right)^{\gamma} < 0$. Hence, there exists a critical value $a = a_c = \frac{(t-c)^{\gamma}}{(t-c)^{\gamma} + \lambda(\theta t + c)^{\gamma}}$ for which $h \mid_{a=a_c} = 0$. Using (3.5), if $a < a_c$, then $D^* = 0$ and if $a > a_c$, then $D^* = W$.

(b) (Fine rate, θ) h is a continuous function of θ on the compact set $\left[0, \overline{\theta} \right]$. We have $\frac{\partial h}{\partial \theta} = -a\lambda\gamma t \left(\theta t + c \right)^{\gamma - 1} < 0$. For $\theta = \theta_c = \frac{1}{t} \left[(t-c) \left(\frac{(1-a)}{a\lambda} \right)^{1/\gamma} - c \right]$ we have $h \mid_{\theta = \theta_c} = 0$. It follows that if $\theta < \theta_c$, $h > 0$, so from (3.5) $D^* = 0$; and for $\theta > \theta_c$, $h < 0$, so from (3.5) $D^* = W$.

(c) (Tax rate, t): h is a continuous function of t on the compact set $[0, 1]$. We have that $\frac{\partial h}{\partial t} = ac\lambda \left(1 + \theta \right) (t-c)^{-1} \gamma \left(\theta t + c \right)^{\gamma - 1} > 0$. For $t = t_c$, where $t_c = c \left(\frac{(1-a)^{1/\gamma} + (a\lambda)^{1/\gamma}}{(1-a)^{1/\gamma} - \theta (a\lambda)^{1/\gamma}} \right) > 0$, we have that $h \mid_{t=t_c} = 0$. It follows that for $t < t_c$, $h < 0$, so from (3.5) $D^* = W$ and for $t > t_c$, $h > 0$, so from (3.5) $D^* = 0$.

(d) (Loss aversion) h is a continuous function of λ on the compact set $\left[0, \overline{\lambda} \right]$, where $\overline{\lambda}$ is the upper limit on the parameter of loss aversion. We have $\frac{\partial h}{\partial \lambda} = -a \left(\theta t + c \right)^{\gamma} < 0$. There exists a critical value $\lambda = \lambda_c = \frac{(1-a)}{a \left(\frac{\theta t + c}{t - c} \right)^{\gamma}}$ for which $h \mid_{\lambda = \lambda_c} = 0$. Hence, using (3.5), if $\lambda < \lambda_c$, then $h > 0$, so $D^* = 0$; and if $\lambda > \lambda_c$, then $h < 0$, so $D^* = W$. ■

Supplementary Section: Experimental Instructions

Welcome

This HIT is different from HITs that you might be used to completing via MTurk. You will be participating in a study about decision making. All responses will be kept anonymous and are for research purposes only. Including the time for reading these instructions, the HIT will take about 30 minutes to complete. Do not close this window or leave the HIT's web pages in any other way during the HIT. If you close your browser or leave the HIT, you will NOT be able to re-enter the HIT and we will NOT be able to pay you! We will express all payoffs in units of an experimental currency, EC. Depending on your choices, you earn different amounts of the experimental currency (ECs). At the end of the task, your payoffs will be converted into real money according to the exchange rate: 100 EC = 1 Dollar. You will receive a code to collect your payoff via MTurk upon completion.

INSTRUCTIONS (Labour Income)

In this experiment you will face three different tasks. In task 1 you will gain some income that depends on your effort in the task. This income is called labour income. In task 2, you will be asked to make choices between risky amounts which we call lotteries (to be explained later) and sure amounts. In task 3, your labour income will be taxed and you will have an opportunity to choose any amount of income to declare for tax purposes. These tasks will be explained in detail in later sections. In addition to $2 participation fee, upon completion of the HIT, you will receive two types of incomes: 1. A guaranteed income of $2 irrespective of the actions that you take. 2. A bonus payment that is described as follows. One of your decisions in the HIT, across all the decisions that you make, is chosen randomly and the income that you earn in that decision constitutes your earnings that will be paid out to you. Every decision you make has some strictly positive chance of being chosen for the payment. Hence, it is important to make all decisions carefully. Please note that decisions determining your income in task 1 are excluded from the bonus payment. You can earn up to $5 in bonuses depending on your choices.

INSTRUCTIONS: Task 1: Labour income task

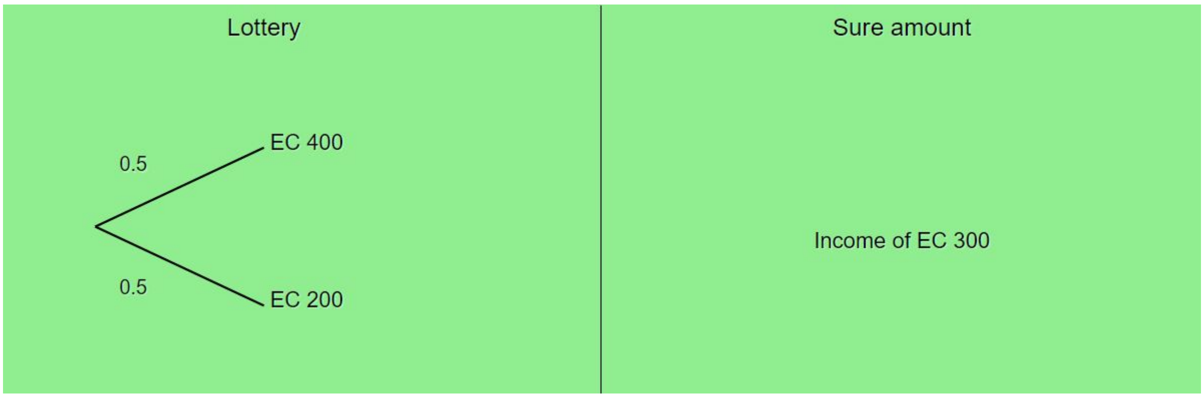
Labour income: You will be presented with 4 series of numbers in which you will need to count the number of 7s or 9s or do some arithmetic correctly in a time bound task. At the end of the task you will get paid EC 50 for each correct answer. These earnings will constitute your labour income. An illustrative example is shown below. Please count the number of 7s. You should enter the number into the empty box below the example.

Example: 5 8 3 6 9 8 6 1 2 8 6 8 7 8 2 5 6 8 6 6 2 7 3 4 5 7 4 7 2 8 1 6 6 9 4 6 4 3 6 2 2 8 4 3 9 7 9 8 5 2 9 2 7 4 8 8 4 9 3 4 3 1 7 3 1 6 7 7 7 2 9 8 5 2 7 2 7 1 7 3 2 3 3 3 1 1 1 3 5 9 7 4 3 5 9 5 2 8 7 3 5 2 5 8 3 2 2 4 9 2 8 1 5 8 1 3 5 2 7 3.

Instruction: Task 2: Lottery choices task

In this task you will be asked to indicate your preferences over risky incomes (which we call lotteries) and sure amounts. The outcomes in these choices are constructed from your earned labour income. Lotteries are shown as decision trees with associated probabilities on the branches (see the figure on the left in the green box below). Suppose your earned labour income is 300. You are offered the choice between keeping your earned labour income for sure (see the figure on the right in the green box below) and playing the lottery below. The lottery offers you two possibilities, each with a 50 percent chance. With a 50 percent chance your income is 400 (i.e., you gain an extra amount 100) and with a 50 percent chance your income is 200 (i.e., you lose an amount 100). Remember there are no objectively right or wrong answers, you only need to indicate your subjective preferences. Also remember that the outcomes of your decisions in the experiment determine your own monetary reward. Once you have made your choice, select the appropriate button at the bottom of the page. The chosen option becomes Blue. You can change your selection before leaving the page. Once you are certain, click Next.

Please note this a practice test. In the actual lottery task (Task 2) you shall be asked to make a series of 12 choices over lotteries and sure amounts in order to gauge your preferences as accurately as possible. If the random question for bonus payment is from this task and you chose the sure amount, you will receive the sure amount. If you chose the lottery, the computer draws a single random number between 1 and 100 that will determine the outcome you will receive. If the random number is between 1 and 50, the outcome is 200. If the random number is between 51 and 100 the outcome is 400.



Instruction: Task 3: Tax payment task

In this task you must decide how much of your earned labour income to declare for tax purposes. We allow you to declare ANY amount for tax purposes. Your earned labour income is taxable at a given income tax rate. If you evade taxes, there is a xreturns will be audited, where x% is any number between 0% and 100%. This number will be told to you. With the remaining probability of 100% minus x% you are not audited, in which case nobody can ever find out that you evaded any taxes. In case, you are audited (with a x% chance), your evasion will be fully discovered by the tax authorities. If your evasion is discovered, you have to pay a fine that is in proportion to the taxes that you have evaded. Please note that your responses will be kept anonymous and are for research purposes only. In this task you have to answer 7 questions. Suppose, as an example that the probability of audit x% is 3%. A 3% audit probability is implemented as follows. The computer randomly draws a single number between 1 and 100. If this random number is either 1, 2, or 3, you will be audited. If the random number is any other number between 4 and 100 you will not be audited. To enhance your understanding of these decisions, the next example takes a given income to show you how the penalty for tax evasion is applied, and the effects on your income.

Illustrative Example

All figures used in this example are for purely illustrative purposes. Suppose your income is 500 and the tax rate on declared income is 30%. So, your legal tax liabilities equal 30% of 500 = 150. If you were to decide to fully pay your taxes, your final income would be 500-150 = 350. If, however, you choose to evade some income, then there is a probability that your tax return will be audited. Suppose that this audit probability is, say, 5% (for other decisions that we shall require you to make, this audit probability may vary). This means that if you evade taxes 100 times, then your tax evasion will be discovered 5 times out of 100 times and it is not discovered 95 times out of 100 times. If your evasion is discovered (with a 5% probability), you will have to pay a fine. Suppose, in this hypothetical example, that the fine equals twice the evaded taxes, i.e., the fine rate is 2 (for other decisions that we shall require you to make, this fine rate may vary). You are allowed to evade any level of income out of your income of 500. Suppose that out of your income of 500 you decide to evade 200 and declare the rest, i.e., 500- 200=300. The tax that you pay on your declared income is 30% of 300 = 90. The evaded tax is 30% of the evaded income of 200 = 60. If your evasion decision is discovered (with 5% probability), you pay a fine equal to twice the evaded tax (remember the fine rate in this example is 2), hence you pay 2 x 60=120 in fines. In sum, should you wish to evade 200 out of your income of 500, then 1. With a 5% chance, you are audited, so your final income is: 500 (initial income) - 90 (taxes paid) - 120 (fine) = 290. 2. With a 95% chance, you are not audited, so your final income is: 500 (initial income) - 90 (taxes paid) = 410.

Please note while you can go back to read the previous instructions, from now once you complete providing your responses on a screen, you cannot return back to that screen in order to revise your answers. So please choose your answers carefully. To proceed, you need to first correctly answer the following test questions.

Suppose you have income of 600 and the tax rate on declared income is 10%, the audit probability is 3%, and the fine rate is 2. Suppose that you decide that you will declare only half of your income for tax purposes (300).

What is the amount of tax that you decide to pay? (tax rate of 10% on declared income of 300)

[ ]

What is the amount of tax that you decide to evade? (tax rate of 10% on evaded income of 600-300=300)

[ ]

If your tax evasion is found out (with a 3% probability), what is the fine you have to pay? (fine rate of 2 on evaded taxes)

[ ]

If your tax evasion is found out (with a 3% probability), what is your final income? (Income of 600 minus taxes paid (see your answer above) minus the fine paid (see your answer above))

If your tax evasion is not found out (with a 97% probability), what is your final income? (Income of 600 minus taxes paid (see your answer above))

If you had decided to fully pay your taxes, what would be your final income? (Income of 600 minus a 10% tax on income of 600)

Task 1: Earnings Task

Count the number of 7s in series 1 and write it in the below box

Series 1: 3 9 9 3 1 1 5 5 7 9 8 2 8 4 4 1 4 1 1 6 1 9 8 8 4 3 2 7 1 4 4 4 4 9 1 6 5 7 1 2 1 3 1 9 2 7 1 8 6 9 8 7 6 1 1 3 5 2 6 9 1 2 8 1 7 8 9 2 1 4 3 4 6 1 6 7 6 1 1 8 5 3 4 2 1 5 9 7 9 5 1 3 2 9 7 1 2 5 4 7 5 5 7 1 8 9 5 7 9 6 2 7 5 3 5 3 3 5 9 5

Count the number of 9s in series 2 and write it in the below box

Series 2: 3 3 5 4 6 4 6 6 2 5 4 3 5 9 2 6 9 2 4 1 1 3 6 6 7 4 1 8 6 8 3 3 1 9 2 5 1 2 8 6 5 9 4 8 8 1 1 4 1 3 6 1 4 2 5 7 1 2 8 5 2 1 2 4 8 2 7 8 4 4 6 2 7 9 8 6 3 6 2 1 5 2 1 1 8 7 2 5 1 4 5 7 6 4 2 3 2 1 5 7 4 9 7 1 1 9 8 1 5 9 7 1 9 1 3 6 3 4 1 9

Count the number of 7s in series 3 and write it in the below box

Series 3: 6 5 9 4 9 9 8 1 7 6 5 7 2 1 6 5 8 3 4 2 5 8 6 6 1 4 4 8 4 7 6 5 4 5 7 1 2 5 8 3 3 8 7 8 1 7 2 9 1 5 4 8 9 8 6 4 5 5 3 3 8 9 5 8 4 6 1 9 2 7 4 9 7 5 2 8 6 6 3 9 6 8 2 9 3 6 6 2 3 2 7 7 5 6 8 4 2 1 6 3 5 2 2 6 9 5 6 5 3 5 9 1 3 4 8 8 1 2 8 4

Count the number of 9s in series 4 and write it in the below box

Series 4: 3 2 8 1 7 7 9 7 4 8 7 2 9 2 1 9 2 3 1 4 1 4 4 9 9 1 7 5 5 4 7 8 6 8 5 4 2 2 9 1 8 5 4 5 6 3 7 3 3 9 8 9 3 5 7 1 2 8 4 8 6 3 3 4 4 5 9 9 1 8 7 2 4 3 7 1 7 5 7 5 8 2 9 3 2 4 2 5 1 2 1 9 7 2 1 4 9 2 3 2 9 5 4 8 4 7 1 7 3 1 6 1 5 1 6 8 8 3 9 3

Multiply the number of 9s in series 3 by the number of 7s in series 1 and write it in the below box

∗∗ Note to the reader: This page does not contain the actual experimental instructions but an explanation in lieu of the instruction ∗∗

The lottery choice task depends on the labor income earned by the subject in Task 1. The subject is offered a set of 6 choices between the labour income for sure, and a risky lottery, as shown on page 2. However, the actual lottery given in the first of 6 choices depends on the endogenous earned income in Task 1. Each of the remaining choices in the series of 6 choices between a lottery and the sure amount are endogenously determined from the previous choice in the sequence of 6 choices. This is explained in full detail in the paper. Due to the endogeneity of the choices in each of the 6 stages, it is not possible to reproduce the experimental instructions, unless done with hypothetical choices, which has already been done in the paper.

Task 3: Questions 1-3

You must now decide how much of your earned labour income to declare for different possible values of the tax rate (5%, 30%, 60%), while the audit probability is 3% and the fine rate is 2. This means that if you evade taxes 100 times, then your tax evasion will be discovered 3 times out of 100 and it is not discovered 97 times out of 100. If you decide to evade an amount E in taxes, the fine that you pay is 2 times E. You will now make decisions on how much of your earned labour income to declare for tax purposes. Please note that your responses will be kept anonymous and are for research purposes only.

Your earned labour income is ...

Your declared income when tax rate is 5%

Your declared income when tax rate is 30%

Your declared income when tax rate is 60%

Task 3: Questions 4-6

You must now decide how much of your earned labour income to declare for different possible values of the fine rate (0,1, 3), while the audit probability is 3% and the tax rate is 30%. This means that if you evade taxes 100 times, then your tax evasion will be discovered 3 times out of 100 and it is not discovered 97 times out of 100. If you decide to evade an amount E in taxes, and if the fine rate is 3, for example, then you have to pay 3 times E as a fine if you get caught. You will now make decisions on how much of your income to declare for different fine rates.

Your earned labour income is ...

Your declared income when fine rate is 0

Your declared income when fine rate is 1

Your declared income when fine rate is 3

Task 3: Questions 7

It is reasonable to suppose that tax evasion is less likely to be detected if you declare more income. Suppose therefore that the probability of detection is 8% if you declare no income. For every additional 50 you declare, the probability of detection falls continuously at the rate of 1So if you declare 50, your probability of detection is 7%; if you declare 100, your probability of detection is 6%; and so on. It follows that if you choose to declare an extra 25, your probability of detection falls by 1/2% and so on. You must now decide how much of your earned labour income to declare, while the fine rate is 2 and the tax rate is 30%.

Your earned labour income is ...

Your declared income:

INSTRUCTIONS (Non-Labour Income)

$**$ Note to reader of paper: The experimental instructions for non-labour income were identical to those for labour income except in one respect. Subjects no longer earned their income. The income was provided by the experimenter. In order to ensure that we had roughly the same proportion of subjects for each income level in both the labour and non-labour income treatments, we relied on the results of our pilot experiments for the frequency of labour earned for each income category. Using these results, we offered subjects in the non-labour income treatment, a random draw of a lottery to determine their income, as described below. In all other respects the two treatments are identical.$**$

Task 1: Income task

Your income will be determined purely by chance according to the lottery (50, 0.40; 100, 0.10; 150, 0.25;200, 0.25). This means that with probability 0.40 you will get 50, with probability 0.10 you will get 100, with probability 0.25 you will get 150 and with probability 0.25 you will get 200. In other words the chance of gaining 50 is 40 percent. The outcome of the lottery will be determined by a random draw. By clicking the button called Draw a number, the computer draws a number between 1 and 100. If the number is between 1 and 40, the outcome is 50. If the number is between 41 and 50 the outcome is 100. if the number is between 51 and 75 the outcome is 150. If the number is between 76 and 100 the outcome is 200. Please press the below button labelled as Draw a number to determine the outcome of lottery and your income.

Draw a Number

You draw ... Hence, your income is ...

End of Experiment•