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Loss Aversion and Tax Evasion: Theory and Evidence

Abstract

We consider income-source-dependent tax evasion and show that this is a generalization of the well-known endowment effect. We show that loss aversion, moral costs, mental accounting, and risk preferences play a key role in explaining key features of source-dependent tax evasion. We provide evidence of the first direct link between subject-specific loss aversion and tax evasion, which is central to most successful modern theoretical accounts of tax evasion. We provide some evidence that risk aversion strengthens the cautionary effect of loss aversion and risk loving behavior attenuates, or reverses, it. However, the underlying effect is also influenced by the source of income. Evasion is increasing in the tax rate and decreasing in the audit penalty, as predicted. Our paper provides novel theoretical insights; proposes new methods in the estimation of the underlying behavioral parameters; and confirms the central predictions of the theory, while pointing out challenges for further developments that existing theory is unable to account for.

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

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

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1 Introduction

Tax evasion is an important area of research within public economics with significant welfare consequences.[1] This problem has attracted a great deal of academic interest.[2] The Allingham-Sandmo (1972) model established the basic framework, based on expected utility, but the empirical success of this framework has been questionable, giving rise to the well-known tax evasion puzzles. The puzzles are both quantitative[3] and qualitative.[4] By contrast, non-expected utility theories such as *prospect theory* provide a far superior explanation of the tax evasion evidence (Bernasconi, 1998; Yaniv, 1999; Bernasconi and Zanardi, 2004; Dhami and al-Nowaihi, 2007, 2010; Eide et al., 2011).[5]

The three aims of our paper, in terms of decreasing order of importance, are described in the next three subsections.

1.1 Loss aversion and tax evasion

The key features in the success of prospect theory in explaining the qualitative and quantitative puzzles in tax evasion is reference dependence and loss aversion. This is true of the theoretical models (Bernasconi, 1998; Yaniv, 1999; Bernasconi and Zanardi, 2004; Dhami and al-Nowaihi, 2007, 2010; Eide et al., 2011; Alm and Torgler, 2012) and of empirical studies that use data from field observational studies (Engström et al., 2015; Rees-Jones, 2018). Loss aversion also influences much human and primate behavior and is also well supported by neuroeconomic evidence (Dhami, 2019, Vol. 1).

Despite the key importance of loss aversion, we are not aware of an empirical work that rigorously and directly measures loss aversion for 'individual' taxpayers and relates it to their tax evasion behavior.[6] Observational studies and studies based on administrative data attempt to study indirect implications of reference dependence and loss aversion, such as bunching of taxpayers where there are kinks in the marginal tax/subsidy rates. Direct measurement of loss aversion at the level of each taxpayer is a specialized, complex, and time consuming, task and

[1]Estimates by the European Commission (2019) show that in 2016 the global offshore wealth was USD 7.8 trillion, or 10.4% of global GDP; the EU share is 9.7% of its GDP. Estimates by the IRS for US data for 2014-2016 show that the average annual tax gap (difference between taxes owed and taxes paid) is $496 billion or 15% of total average annual federal taxes owed.

[2]For surveys of the voluminous literature, see Andreoni et al. (1998), Slemrod and Yitzhaki (2002), and Alm (2019).

[3]Using the existing real-world parameters of detection and enforcement, the rate of return from a unit of tax evaded is 95–95 percent, yet we observe only 30–40 percent of tax evaders who do have a chance to evade, do evade (Skinner and Slemrod, 1985; Yaniv, 1999). In particular, expected utility provides quantitative predictions that are in error by a factor of up to a 100 (Dhami and al-Nowaihi, 2007).

[4]Under reasonable assumptions, an expected utility analysis predicts that an increase in the tax rate reduces tax evasion, which is not empirically supported. See, for example, Friedland et al. (1978), Clotfelter (1983), and Andreoni et al. (1998). For a contrary result, see Feinstein (1991). This is known as the Yitzhaki puzzle (Yitzhaki, 1974). The Yitzhaki puzzle can be explained using prospect theory (Dhami and al-Nowaihi, 2007).

[5]*Rank dependent utility theory* cannot explain all the paradoxes in the tax evasion literature (Dhami, 2007, 2010; Eide et al., 2011). In particular it lacks a reference point and the parameter of loss aversion, which reduce its explanatory power.

[6]In their survey and meta-analysis of tax evasion experiments, Alm and Malezieux (2021) state "To the best of our knowledge, comparing tax evasion behavior with a measure of loss aversion has not been implemented in the lab before."

requires measurement of all parameters of prospect theory in one fell swoop.[7]

The 'main aim' of our paper is to provide direct confirmation of the underlying mechanisms of prospect theory based explanations of tax evasion, by directly measuring individual-specific loss aversion in lab experiments. We then relate individual-specific loss aversion with the tax evasion decisions of the same individual.

1.2 Source-dependent evasion

Extensive evidence shows that humans experience different levels of *entitlements* from earned and unearned incomes.[8] In the classic endowment effect studies, entitlements are themselves caused by loss aversion (Kahneman and Tversky, 2000; Dhami, 2019, Vol. 1). We wish to examine the income-source-dependence of tax evasion (source dependent evasion) when the different income sources are identical in their tax/detterence treatment. In particular, we compare *labor income*, *earned* in a tedious experimental task, relative to *non-labor income* which is *unearned* during the experiment, e.g., bequests, gifts, lottery wins, unexpected capital gains. Our proposed theory allows for potentially any difference in the two income sources, provided the individual feels more entitled to one income source over the other.

If taxpayers evade different amounts from the two different sources of incomes then this may also indicate a form of *mental accounting*. 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*".[9] Source-dependent tax evasion behavior, if confirmed, potentially indicates mental accounting because tax evaders then appear to code and categorize different income sources, identical in their tax/deterrence treatment, differently.[10]

It is an interesting research question to see if there is any interaction between the source of income, loss aversion, and risk aversion. This is the second objective of our study.

Following the earlier literature, cited above, we hypothesize that people feel more entitled to (earned) labor income relative to (unearned) non-labor income. We conjecture two effects, working in opposite directions, through which entitlements to income might influence tax evasion. (i) First, loss aversion arising from being caught evading taxes is greater from income that one feels more entitled to (earned income) relative to unearned income, and our data supports it. Our theoretical model shows that higher loss aversion reduces evasion. Hence, individuals should *evade less earned income* as compared to unearned income. (ii) Second, we hypothesize

[7] For a survey of the alternative methods of measurement, see Wakker, (2010) and Dhami (2019, Vol. 1).

[8] See, for instance, Hoffman and Spitzer (1982); Cherry et al. (2002); List and Cherry (2000). In dictator game experiments, when income is earned, dictators reduce the amount transferred (Cherry et al., 2002; Cappelen et al., 2007); and when income of the receivers is earned, dictators increase the amount transferred (Oxoby and Spraggon, 2008). The distinction between earned and unearned income also influences proposer offers and the rejection rates of responders in ultimatum games (Lee and Shahriar, 2017, Dhami et al., 2020).

[9] The evidence suggests that (i) individual behavior in many domains is dependent on the source of income, and (ii) incomes and expenditures are not fungible across different *mental accounts* (Kahneman and Tversky, 2000; Thaler, 1999); for a survey of the literature, see Dhami (2020, Vol. 5, Ch. 2).

[10] In this case, money is *not fungible* across different sources of income (identical in their tax/deterrence treatment) in the following sense. Individuals who have the same combined income from the two sources, but receive different proportions of these two sources of income, will have different post-tax income, because their evasion is source-dependent. Hence, although we do not examine this channel, they are also likely to differ in their savings and consumption levels. This has potential welfare consequences that that do not arise in the absence of mental accounting.

that there are lower moral cost from evading earned labor income. Our theoretical model predicts that lower moral costs from evasion will result in more evasion of labor income. There is no satisfactory method of directly measuring income source-specific moral costs for each taxpayer, but we provide indirect evidence, consistent with moral costs.[11]

From (i) and (ii) above, greater loss aversion *reduce*s evasion and lower moral costs *increase* evasion of earned income. Thus, the overall *treatment effect*, which determines the relative tax evasion from labor and non-labor income, is an empirical question.[12] We note that, nevertheless, a predicted ambiguous result is also an important theoretical result that needed to be demonstrated rigorously. Furthermore, the sign of the treatment effects, based on our empirical analysis, speak to the relative strengths of the two opposite effects.

1.3 Loss aversion and risk aversion

Traditional analyses of risky situations, based on expected utility theory, highlight the importance of risk aversion in explaining individual choices.[13] By contrast loss aversion is a property of the utility function under prospect theory, not related to its curvature, and it arises in riskless choices as well as risky choices. Risk aversion and loss aversion are distinct, yet related, entities on prospect theory.[14]

There are claims that once loss aversion is accounted for, there is 'no' remaining risk aversion (Novemsky and Kahneman, 2005). In other words, the claim is that observed risk aversion is likely to be mostly on account of loss aversion, but unless one separately measures them, results may be confounded. There is no simple relation between risk aversion and loss aversion under prospect theory if there are outcomes in, both, the domains of gains and losses. However, we measure risk aversion in lotteries that are only in the domain of gains, while loss aversion is measured with both gain and loss lotteries; this removes the confounding role of loss aversion.

A third aim of our paper is to measure risk aversion for each individual taxpayer and relate it to evasion behavior, while also considering the interactions between risk aversion and loss aversion.

1.4 Theoretical model

We use the framework in Dhami and al-Nowaihi (2007, 2010) to derive the implications of loss aversion and income-source dependence of tax evasion, using prospect theory. Since these results follow in a straightforward manner from their model, we relegate the detailed model to the supplementary section, and only list the two main propositions in the text as a guide to the

[11]Neuroeconomics might eventually enable direct measurements of morality costs (Yoder and Decety, 2018).

[12]An analogy might help. Consider the opposing income and substitution effects in problems of labor supply that might render a weak overall wage effect on labor supply. Yet, it is important to identify the separate income and substitution effects for various policy reasons, for instance, to identify the deadweight loss of a distortionary wage tax from the substitution effect alone.

[13]Risk aversion is a property of the curvature of the utility function in an expected utility analysis. However, under prospect theory, the shapes of the utility function and the probability weighting function jointly determine risk attitudes.

[14]In order to measure risk aversion, the relevant calculation of certainty equivalent incorporates the shape of the utility function and, hence, the parameter of loss aversion. This creates a measurement confound between the two.

predictions of the relevant model.

1.5 Experiments and findings

We ran a between-subjects experiment over Zoom with Indian University students. Subjects are randomly assigned to either a primed or an unprimed group. The primed group is shown data about tax evasion in India. Within each group, subjects are assigned to two treatments. In the first treatment (T1), taxpayers have only non-labor, experimenter-provided, unearned income. In the second treatment (T2), the only source of income for taxpayers is labor income, earned by solving a set of timed and tedious experimental tasks. We control for taxpayer-specific preference characteristics (e.g., loss aversion, risk attitudes), economic characteristics (e.g., education), and demographic characteristics (e.g., age, gender, marital status, religion). In addition, we explore the effects of varying the tax and detection/enforcement parameters on tax evasion.[15]

Several empirical results support the predictions of our theoretical model. In the simplest estimation, under a linear utility function, the mean loss aversion for our data is 1.83. For a non-linear utility function, the mean loss aversion is 1.37 for non-labor income and 1.53 for labor income. This supports our conjecture on source dependent loss aversion.

Even when there is an effective 100% subsidy to evasion, taxpayers declare, on average, 35% of their income, which is consistent with the presence of moral costs of evasion.[16] Moreover, in the presence of a subsidy to evasion, unprimed subjects declare, on average, more of their non-labor income, which is consistent with our hypotheses on income-specific differences. However, we do not measure moral costs for different sources of income.[17]

In terms of "direct effects" in a Tobit regression, those who are loss averse, declare 18.0 percentage point more of their income, relative to those who are loss seeking. This is consistent with our theory. It also provides the first direct empirical evidence, using subject-specific, directly measured, loss aversion, for the underlying transmission channel in most 'prospect theory based' explanations of tax evasion, as described above.

Yet, we show that the effects of loss aversion are more complicated than anticipated. They are influenced by the source of income (as postulated), but also by risk preferences, which is a new result that cannot be accommodated within the predictions of our theoretical model, or any other decision theory model that we are aware of. Loss averse and risk averse taxpayers

[15] These parameters are common to both sources of incomes, which is difficult, or impossible, to obtain in observational/field studies of tax evasion. We also consider values for these parameters that are also difficult to obtain in observational/field studies, and these variations give us important economic insights.

[16] 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 also possible that moral costs capture some underlying personal moral norms. We are grateful to James Alm for raising this point.

[17] Our results can only provide 'indirect' evidence for source-specific moral costs. 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.

declare 7.6 percentage point more labor income relative to non-labor income. However, loss averse and risk loving subjects declare 19.2 percentage point less labor income, relative to non-labor income. It is 'as if' risk loving behavior reverses the cautionary effects of loss aversion on declared incomes for labor income. Loss seeking and risk averse subjects declare 3.5 percentage point more labor income as compared to non-labor income. In this case, the cautionary effects of risk aversion seem to overweight the effects arising from loss seeking behavior. However, this is not a general finding, as we also report exceptions depending on the source of incomes. For instance, risk loving and loss seeking subjects still declare 5.0 percentage point more labor income relative to non-labor income.

In conjunction, our results show that entitlements are driven not just by loss aversion, but also by moral costs, mental accounting, and risk preferences.

Finally, we confirm some of the standard effects that have already been identified or tested in other models. 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, and we confirm this with our data. We also show that evasion is decreasing in the tax rate, as predicted by prospect theory, where no Yitzhaki puzzle arises.

1.6 Schematic outline of paper

Section 2 presents our model. Section 3 summarizes the theoretical 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 audit penalty rate and the tax rate. Section 8 gives a Tobit analysis of the proportion of declared income and highlights its determinants. Section 9 concludes. We provide the details of all the theoretical results in the paper and some additional statistical findings in a separate supplementary section.

2 The Model

We use the generic Allingham-Sandmo-Yitzhaki model of tax evasion, adapted to prospect theory by Dhami and al-Nowaihi (2007). We relegate the full model and the derivations to the supplementary section.[18] We summarize the essential features of the model in this section, and the theoretical predictions in the next section.

We distinguish between the source of the taxable income, i.e., either *labor income*, L, or *non-labor income*, N. We write the income of the taxpayer from source $j = L, N$ as W_j. In our experiments, the taxpayer either has labor income ($j = L$) or non-labor income ($j = N$), but never both. Hence, we may conserve notation further and dispense entirely with the subscript j and refer to the taxpayer as having unobserved taxable income W.

[18]Note, however, that Dhami and al-Nowaihi (2007) do not incorporate morality costs in their paper, nor source-dependent tax evasion. Nor do they consider the countervailing effects of loss aversion and morality costs. Their interest was in simulation results with non-experimental data and treatment effects are absent from their paper.

Each source of income is taxed at the identical constant marginal rate t, $0 < t < 1$. The taxpayer chooses to declare income $D \in [0, W]$ and evades the amount $W - D$. The two deterrence parameters, audit probability, p, and the penalty rate, θ, are also identical for the two sources of incomes. Taxpayers are audited with the probability $p(D) \in [0, 1]$, such that

$$p(D) = a - bD; a \in [0, 1], 0 \leq b \leq \frac{a}{W}. \tag{2.1}$$

The restrictions on a, b ensure that $p(D) \in [0, 1]$ for all $D \in [0, W]$. We term the case $b = 0$, so $p(D) = a$, as 'exogenous' audit probability; and the case $b > 0$ as 'endogenous' audit probability because it depends on declared income (an endogenous decision). An audit provides observable and verifiable information to the tax authorities on the true income, W. If caught, a tax evader must pay the outstanding tax liabilities $t(W - D)$, and a penalty $\theta t(W - D)$, where θ is the *penalty rate* on evaded taxes. If $\theta < 0$, then the government effectively subsidizes tax evasion. In our experiments, we show that for $\theta = -1$ (100% subsidy to the taxpayer if caught evading), there is significant declared income, which is consistent with underlying moral costs of evasion. However, our main case of interest is $\theta > 0$. Thus, if caught, the taxpayer pays the following amount to the tax authorities

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

We call f the *fine rate* per unit of evaded taxes. A tax evader experiences morality costs $c \in [\underline{c}, \bar{c}]$ per unit of evaded taxes, *irrespective of whether caught or not.* We assume that (i) morality costs are non-negative ($\underline{c} \geq 0$), and (ii) no higher than the tax rate.[19]

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' serves as 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) provides a useful, and empirically satisfactory, reference point and enhances the status-quo in applications, particularly tax evasion (Dhami and al-Nowaihi, 2007, 2010).[20] For this reason, we define the reference income, R, of the taxpayer to be the legal after-tax income

$$R = (1 - t)W.$$

Dhami and al-Nowaihi (2007) show that this is the 'unique' reference point such that for any level of declared income, $D \in [0, W]$, the taxpayer is always in the domain of gains if not caught evading, and in the domain of losses if caught evading taxes.[21] We use the standard prospect

[19]This is a purely technical assumption, and ensures that the objective function is always real-valued; see the supplementary section.

[20]Reference points based on fairness/social norms play a major role in many phenomena. 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. 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 (Dhami and Sunstein, 2022). Furthermore, we lack decisive empirical evidence that reference points are consistent with rational expectations, although evidence suggests they are expectations-based (Dhami, 2019, Vol. 1, Section 2.8.3).

[21]This is an attractive property and enables them to explain the existing qualitative and quantitative puzzles on tax evasion. It would be perverse if the taxpayer were not in the domain of losses despite being caught evading taxes and levied with a significant penalty.

theory utility function (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), which has axiomatic foundations (al-Nowaihi et al., 2008):

$$v(x) = \begin{cases} (x)^{\gamma} & if \quad x \geq 0 \\ -\lambda(x)^{\gamma} & if \quad x < 0 \end{cases}, \tag{2.3}$$

where x is an outcome relative to a reference point. The typical restriction on the two parameters in (2.3) are $0 < \gamma < 1$ and $\lambda > 1$ (loss aversion). But in our empirical exercise we also allow for $\lambda < 1$ (loss seeking).

As discussed in the introduction, earned labor income may create greater entitlements relative to unearned non-labor income through differences in loss aversion and moral costs of evasion. A formal statement of this assertion requires us to temporarily invoke the subscript $j = L, N$ for the source of income that was suppressed above. Let c_j, λ_j denote, respectively, moral cost of evasion and loss aversion for the taxpayer from income source $j = L, N$. Then, the taxpayer exhibits relatively lower moral cost of evading labor income to which the taxpayer feels more entitled to

$$c_L < c_N, \tag{2.4}$$

and relatively higher loss aversion from labor income (giving up a unit of income that one feels more entitled to, is more aversive).

$$\lambda_N < \lambda_L. \tag{2.5}$$

We allow for individual-specific and income-source-specific heterogeneity in preference parameters, but suppress it in the formal notation.

3 Theoretical predictions

We now directly give the theoretical predictions of the model. The details of the derivations are in the supplementary section. There are two states of the world. (1) $s = C$ if the taxpayer is 'caught' evading taxes. (2) $s = NC$ if the taxpayer is 'not caught' evading taxes.

Proposition 1 *Consider an interior solution to optimal declared income $D^* \in (0, W)$ and an endogenous probability of detection $p(D) = a - bD$, $a \in [0, 1]$, $b > 0$.*[22]
(a) (Effectiveness of deterrence) D^* is increasing in the penalty rate, i.e., $\frac{\partial D^*}{\partial \theta} > 0$, and in the probability of detection parameter, a, 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., $\frac{\partial D^*}{\partial c} > 0$.

Discussion of the results: An increase in the probability of detection (the parameter 'a'), or an increase in the audit penalty, θ, reduce the expected marginal returns from evasion, which reduces evasion (Proposition 1a). An increase in loss aversion increases the losses that arise in

[22] For an extension of these results to corner solutions, see the supplementary section.
[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.

the state $s = C$, when caught evading taxes, reducing the marginal return from evasion, hence, reducing evasion (Proposition 1b). Prospect theory predicts that as the tax rate increases, evasion increases, in conformity with the available evidence, so there is no Yitzhaki puzzle under prospect theory (Proposition 1c).[24] This is a simple extension of the result in Dhami and al-Nowaihi (2007). Finally, an increase in the moral cost, c, of tax evasion reduces evasion by reducing income relative to the reference point in both states of the world (Proposition 1d).

Recall from (2.4) and (2.5) our hypotheses that for earned labor income, loss aversion is relatively higher ($\lambda_N < \lambda_L$) and moral costs of evasion are relatively lower ($c_L < c_N$). From Proposition 1b an increase in loss aversion reduces evasion and from Proposition 1d, a reduction in moral costs increases evasion. Since these effects oppose each other, depending on the relative strengths of the two effects, the treatment effect (relative evasion in the two treatments) can be positive, zero, or negative. Thus, the treatment effect is an entirely empirical question.

We now show how the result in Proposition 1 is modified with an exogenous probability of detection, $p(D) = a > 0$ (and $b = 0$), that is independent of the amount evaded; we consider this case in some of our experimental questions. In this case, we get a bang-bang solution in which the optimal declared income, D^*, responds to critical values of the parameters and the policy parameters. However, the intuition for the comparative static effects is as in Proposition 1, which we do not repeat here.

Proposition 2 *: Suppose that the probability of detection is exogenous, so that $p(D) = a > 0$, 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 $\theta \in [0, \bar{\theta}]$, where $\bar{\theta}$ is the maximum possible penalty rate. Then there exists a critical value of $\theta = \theta_c > 0$ such that if $\theta < \theta_c$, $D^* = 0$, and if $\theta > \theta_c$, $D^* = W$. At $\theta = \theta_c$, 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 $t < t_c$, $D^* = W$, and for $t > t_c$, $D^* = 0$. At $t = t_c$, we have $D^* \in [0, W]$.
(d) (Loss aversion, λ) 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 $D^* = W$. At $\lambda = \lambda_c$, we have $D^* \in [0, W]$.

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*[25] and (2) the *bisection method* for generating indifference between lotteries (Abdellaoui, 2000) applied to our problem. We also compute the *risk attitudes* of subjects.

[24] This was first shown in Dhami and al-Nowaihi (2007). 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).

[25] We use the income from the relevant treatment (labor or non-labor income) for each of these tasks, separately. So if a subject has, say, the labor income y, then this income is used once in the lottery task and again in the tax evasion task.

4.1 Theoretical framework for estimating loss aversion

Suppose that the income of the subject is y, which could either be in treatment T1 or T2. We assume that the reference income, r, of the subject is the status-quo income, so $r = y$ (and this is made salient in the experimental instructions).[26] We fix an experimenter-provided outcome $z > 0$ and a probability $p > 0$. We then elicit the outcome value $x > 0$ for which the subject expresses indifference between the following two lotteries:

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

Lottery L_1 allows the subject to keep the income y for sure. In lottery L_2, the subject gains an amount $x > 0$ with probability $1 - p$ and loses an amount z with probability p. Only for this calculation, we allow for non-linear probability weighting.[27] We denote the prospect theory evaluation of lottery L by $V(L)$. We use standard methods for the evaluation of lotteries under prospect theory (Wakker, 2010, Dhami, 2019, Vol. 1). Since $r = y$, hence, in lottery L_2, we have one outcome in gains and one in losses. Using the prospect theory utility function v, defined in (2.3) and $v(0) = 0$, it is straightforward to derive the expressions below

$$V(L_1) = v(y - r) = 0$$

$$\begin{aligned} V(L_2) &= w(p)v(y - z - r) + w(1 - p)v(y + x - r) \quad \text{[Using prospect theory]} \\ &= w(p)v(-z) + w(1 - p)v(x) \quad \text{[Using } r = y\text{]} \\ &= -\lambda(z)^\gamma w(p) + x^\gamma w(1 - p) \quad \text{[Using (2.3)]}. \end{aligned}$$

Thus, the indifference in (4.1) implies that $V(L_1) = V(L_2)$, or $0 = -\lambda(z)^\gamma w(p) + x^\gamma w(1-p)$, 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

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

We obtain an identical result using linear probability weighting ($w(p) = p$).[28]

Remark 1 : *(a) In our experiments, the elicitation of loss aversion in this section is carried out 'for each individual taxpayer' and separately for each treatment. Hence, (4.3) written in full notation is* $\lambda_{ij} = \left(\frac{x_{ij}}{z}\right)^{\gamma_{ij}}$ *where* $j = L, N$ *is an index for the income source, and* i *is a taxpayer index.*

[26] Recall that this is the lottery choice task, and not the tax evasion task. Notice that in the tax evasion problem, the status-quo income is the post-tax income, while there are no taxes in the lottery choice task, hence, the relevant status-quo income is y.

[27] A *probability weighting function* is a strictly increasing function $w : [0, 1] \to [0, 1]$. For a detailed exposition of its properties and on its use in prospect theory, see Dhami (2019, Vol. 1). Our results also hold for the special case of $w(p) = p$, but our method (see below) shows that our results are reasonably robust to other probability weighting functions.

[28] In our econometric analyses we show that our results are robust to these assumptions. First, we use a binary measure of loss aversion to mitigate the effect of probability weights. Second, we estimate loss aversion under various assumptions on probability weights. See the results reported in the supplementary section, and particularly Table 3 in the supplementary section.

In (4.3), there are two unknowns on the RHS, x and γ (recall that z was chosen by the experimenter in (4.1)). In Section 4.2 below, we show how to elicit x; and in Section 4.3 below we show how to approximate the preference parameter, γ, of a subject with income y.

We now describe our theoretical framework for the calculation of γ. We elicit the certainty equivalent value C such that a subject exhibits the following indifference

$$C \sim (y, 0.5; 2y, 0.5). \tag{4.4}$$

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). The reference income equals the status-quo income y ($r = y$), so $C \in [y, 2y]$. Using $r = y$, the prospect theory utility function v, defined in (2.3), and $v(0) = 0$, the indifference in (4.4) implies the following prospect theory calculation[29]

$$\begin{aligned} v(C-y) &= [1 - w(0.5)]v(y-y) + w(0.5)v(2y-y). \\ &\Rightarrow v(C-y) = w(0.5)v(y). \end{aligned} \tag{4.5}$$

The two-parameter 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 tax evasion simulations in Dhami and al-Nowaihi, 2007). Evaluated at these parameter values, $w(0.5) = e^{-0.8(-\ln 0.5)^{0.45}} = 0.507$. Subject-specific estimation of α, β is a very challenging process, so we do not carry out this exercise. Hence, we use the approximation $w(0.5) \approx 0.5$. In our empirical exercise, we successfully check the robustness of our results to other values of the probability weighting function.

Using (2.3), and the approximation $w(0.5) \approx 0.5$, (4.5) implies $(C-y)^{\gamma} = 0.5(y)^{\gamma}$. Solving for γ we get

$$\gamma \approx \frac{\log(0.5)}{\log\left(\frac{C-y}{y}\right)}. \tag{4.6}$$

4.2 Estimation of x using the bisection procedure

In this section, we outline the subjective estimation of x in (4.3) following the bisection method in Abdellaoui (2000). Consider the two lotteries L_1 and L_2 in (4.1), where y, z, and p are fixed. It is clearer to denote L_2 by $L_2(x)$. Our objective is to find x after offering subjects a series of 6 lottery choices of the following form.

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 $x_1 \in [0, 5z]$ 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 $[0, x_1]$ (we bisect the interval in each choice,

[29] Note that in this case, both outcomes are in the domain of gains, so the decision weights need to be cumulated in the gains domain (Wakker, 2010; Dhami, 2019, Vol. 1).

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 $[x_1, 5z]$; 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 in the next step by reducing x_2 to x_3, which 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 either the midpoint of the interval $[x_2, 5z]$ (if L_1 was chosen in Choice 1) or $[x_2, x_1]$ (if $L_2(x_1)$ was chosen in Choice 1).

3. Choice $k = 3, 4, 5, 6$: 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 the previous $k - 1$ choices. Thus, the interval containing x shrinks by either replacing the lower bound or the upper bound of the feasible interval in each iteration based on subjects' choices. The feasible interval in each iteration is contingent on all previous choices.

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 4.2). Then, in order to approximate γ in (4.6), we elicit the value C such that the indifference in (4.4) holds. We employ the bisection method with 6 iterations, as in Section 4.2.

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.

5 Experimental Design

Our experiments were conducted between March and November 2022 over one-on-one zoom sessions with the experimenter.[30] We recruited 525 students from various universities in India. The experiment was programmed in LIONESS, developed by Giamattei et al. (2020).

The payments to the subjects had three components. A show-up fee of Rs. 100; and two incentive payments, contingent on choices in the two tasks (lottery choice task and the tax payment task). On average, subjects took 35 minutes to complete the experiment. The

[30] From March to November we respectively collected 153, 26, 38, 31, 81, 19, 67, 50, 11 responses in each month.

average payment per subject was Rs. 244; thus, the per hour payment, on average, was Rs. 418.[31] Subjects were assured of strict anonymity of their choices. All subjects were paid in private after the experiment through an automated process which excluded the experimenter, and subjects knew this.

We used a between-subjects design to derive the contrast between our treatments. Subjects are randomly assigned to primed and unprimed groups. Subjects in the primed group are asked to read a factually accurate but fairly extreme description of tax evasion in India, with potentially important implications for the provision of critical public services in India.[32]

Within the primed and unprimed groups, subjects were randomly allocated to one of the two treatments.[33] In treatment T2, subjects could earn 'labor income' by performing a tedious task that required them to count the number of 7s and 9s in different sequences of densely packed numbers in 225 seconds. Based on the number of correct answers, subjects could earn one of the following levels of labor income: 25, 50, 75, 100, 125. To keep the distribution of subjects for each income level comparable in the two treatments, in treatment T1 we randomly allocated subjects to unearned non-labor income levels of 25, 50, 75, 100, 125, using an earlier pilot. This successfully ensured comparable frequencies of subjects for each income level in the two treatments.

Once the income of the subjects was determined (Task 1), they participated in the following two main tasks (Tasks 2 and 3) whose order was randomized. (1) A *lottery task* that was designed to elicit loss aversion, and (2) a *tax payment task* in which subjects made a tax evasion decision. We now explain these tasks.

The lottery task

The lottery task was conducted using the income of the subjects from Task 1 (non-labor income in T1 and labor income in T2). The elicitation of the loss aversion parameter, for each subject, is implemented using the process described in Section 4.

The tax payment task

Using either their non-labor income (T1) or labor income (T2), we asked subjects to declare their income for tax purposes in response to the following 7 questions. The order of these questions was randomized through a Latin Square Design. For the audit probability function in (2.1), $p(D) = a - bD$, $a, b \geq 0$, we have the following two cases of, respectively, exogenous and endogenous probability of detection. (i) For Q1–Q6, $a > 0, b = 0$, so $p(D) = a$. (ii) For Q7, $a > 0, b > 0$. Note that for most amateur tax evaders, the detection probability ranges between 1% to 5% and the penalty rate θ ranges between 0.5 to 2 (Skinner and Slemrod, 1985). However,

[31]Using the exchange rate \$1 = Rs. 82.38, at the time of the experiments, the average per hour payment was \$5.07.

[32]Subjects read the following description in the primed treatment. "On February 12, 2020, the income tax department stated that only 1.46 crore Indians pay the full tax on their income [1 crore = 10 million]. Relative to the total population of India, this implies that only about 1.1% of Indians pay the full income tax. The 15th Finance Commission of India analysed the structural tax gap in India and pegged the difference in potential tax collections and real tax collections to be over 5% of GDP. In the fiscal year 2020-2021, the government budget targeted income tax collection of 5.69 lakh crores, while the actual tax collections between April to September were only 2.13 lakh crores. In other words, the actual income tax collection was not even 40% of the target."

[33]At the beginning of the experiment, subjects were chosen randomly to be assigned a unique ID number. Odd numbered subjects participated in treatment T2 and even numbered subjects participated in treatment T1.

in several cases, we explore an even larger range of parameter values in order to achieve a better understanding of the underlying reaction functions of the taxpayers.

1. Questions Q1–Q3 ask subjects to declare their income for 3 different values of the tax rate (5%, 30%, and 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 values.

2. Questions Q4–Q6 ask subjects to declare their income for 3 different values of the fine rate $f = 1+\theta$ (0, 1, and 3). We hold fixed the audit probability at 3% and the tax rate at 30%; these are empirically realistic values. When $f = 1$, the effective penalty rate is $\theta = 0$ (tax evaders who are caught, pay back just owed taxes), 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 (if caught, the tax evader pays nothing, not even owed taxes).

3. Question Q7 asks subject to declare their income under an endogenous detection probability, $p(D) = a - bD$, $a > 0, b > 0$.[34] Thus, the probability of audit is decreasing in declared income. The fine rate is held fixed at $f = 2$ and the tax rate at 30%, which are empirically realistic values. We use the parametrization

$$p(D) = 0.08 - 0.0004D, \tag{5.1}$$

so $a = 0.08$ and $b = 0.0004$, which satisfies the restrictions in (2.1). Thus, starting with an exogenous probability of detection of, say, 8%, for every increase in declared income, D, of 25, the probability of detection decreases continuously by 1%. As an example, for someone with an income of 125, who declared their entire income, the detection probability is 3%.

Since the probability of detection is kept fixed for Q1–Q6, the relevant predictions of our model are contained in Proposition 2. Q7 enables us to test the prediction of our more general model (see Proposition 1) based on an audit probability that is decreasing in the amount declared.

Several illustrative examples were given to the subjects to enhance their understanding of the experiments. Subjects also had to answer non-trivial test questions correctly to proceed in the experiment.

6 Descriptive statistics

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

6.1 Basic data on participation and evasion

Out of 525 people who completed the experiment, 31 people participated twice and we only considered their first attempt. For 3 subjects we have some NAs due to software issues and 14 subjects were not students. Dropping these individuals, we have a sample size of 477.

[34] Recall that our definition of endogenous detection probability only requires that $b > 0$, so that the actual probability of detection depends on the amount that a taxpayer (endogenously) decides to declare.

Table 1: The number of subjects in each income category for each treatment

Treatments/Income levels	25	50	75	100	125	mean	median
Primed & labor (n=120)	10	12	29	29	40	91	100
Primed & Non-labor (n=121)	27	9	24	21	40	82.9	100
Unprimed & labor (n=126)	17	18	21	42	28	84.1	100
Unprimed & Non-labor (n=110)	17	6	21	32	34	88.6	100

The number of subjects in each category of income (25, 50,75, 100, 125) for each treatment is shown in Table 1. There is a reasonably similar frequency of subjects in each treatment and the median of income is the same across all 4 treatment arms.

Table 2: Percentage of declared income for each question

Treatments		Q1 ($t = 5\%$)	Q2 ($t = 30\%$)	Q3 ($t = 60\%$)	Q4 ($f = 0$)	Q5 ($f = 1$)	Q6 ($f = 3$)	Q7 *
Primed & labor	Mean (Median)	81(100)	67(72)	53(50)	36(18)	51(50)	80(100)	75(80)
Primed & Non-labor	Mean (Median)	78(100)	64(68)	50(40)	32(0)	48(48)	75(96)	74(93)
Unprimed & labor	Mean (Median)	77(100)	59(60)	49(47)	34(6)	45(40)	76(99)	73(80)
Unprimed & Non-labor	Mean (Median)	79(100)	66(71)	53(50)	40(24)	48(50)	74(96)	69(80)

* For Q7 the probability of audit is decreasing in declared income with $t = 30\%$ and $f = 2$. For Q1–Q6 the audit probability is fixed at 3%. For Q1–Q3, the fine rate is fixed at $f = 2$ and for Q4–Q6 the tax rate is fixed at $t = 30\%$.

In Table 2, we report the mean and the medians of the percentage of declared incomes, across all subjects, in all income categories, for each of our 7 questions (see Section 5 for a detailed description of the questions).

As noted earlier, due to the opposing effects of loss aversion and morality, the overall treatment effects are an empirical question (for an econometric analysis, with controls, see Section 8 below). Yet, positive treatment effects (lower evasion for labor income) will indicate to us that loss aversion plays a relatively more important role than moral costs of evasion. In Table 2, there are examples of significant differences in evasion across treatments that should not arise in the absence of source-dependent evasion, or mental accounting. In Q2, and for unprimed subjects, there is a statistically significant difference in declared incomes across the two income sources (3^{rd} and 4^{th} rows of column labeled Q2) with $p = 0.0396$.[35] In Q6, and for primed subjects, there is a statistically significant difference in declared incomes across the two income sources (1^{st} and 2^{nd} rows of column labelled Q6) with $p = 0.0458$.

Across all questions, once primed, subjects declare more labor income (58%) as compared to non-labor income (51%). Among the unprimed group, subjects declare more non-labor income as compared to labor income in Q1–Q5.[36]

[35] We do not create new notation for p-values, as distinct from the probability of detection $p(D)$

[36] The data that we provided in our priming exercise are factual, but fairly extreme. We tell subjects that only about "1.1% of Indians fully pay income tax." Note that a large percentage of Indians do not have incomes exceeding the required threshold to pay taxes. Priming induces people to evade slightly less taxes in our experiments, perhaps with the correct realization that many social services may simply collapse if not enough taxes are paid. If our priming text had given subjects less extreme figures, it is possible that it might have increased tax evasion. However, as noted in the introduction, our main interest in this paper does not lie in the specific effects of priming, and it is not one of the three objectives of this study listed in the introduction.

In order to compare the differences in declared incomes arising from exogenous and endogenous probabilities of detection (respectively the cases $a > 0$, $b = 0$ and $a, b > 0$), keeping fixed tax rates and penalties at empirically realistic levels (30% tax rate and a fine rate of 3), we compare the results for Q2 and Q7. For the unprimed group, the difference between declared incomes in Q7 and Q2 is greater for labor income as compared to non-labor income ($73 - 59 = 14$ in 3^{rd} row as compared to $69 - 66 = 3$ in 4^{th} row).

We provide details on the corner solutions ($D = 0$, $D = W$) in the supplementary section; here we note some of the findings. The only treatment differences are for Q2. For Q2, and for the unprimed group, there is a statistically significant difference between the proportion of subjects who declare full incomes ($D = W$) from the two income sources with $p = 0.02421$. Thus, when faced with empirically realistic values of the policy parameters (tax rate of 30% and fine rate f of 2), subjects fully declare more of their non-labor income as compared to their labor income.

Recall that we randomized the order between Tasks 2 and 3 (lottery task and tax payment task). No order effects were found in our data. There is no statistically significant difference in the percentage of declared incomes across all 7 questions between those who faced the lottery task first and those who faced the tax payment task first. The $p-$values from the t-tests for the differences in declared incomes for the 7 questions (Q–Q7) in chronological order are: $0.715, 0.180, 0.257, 0.280, 0.233, 0.564, 0.797$.

6.2 Loss aversion and risk aversion

Our measurement of loss aversion is described in Section 4; see equation (4.3). Our estimates of mean and median loss aversion are 1.46 and 1.06 respectively.[37] This figure is lower than other estimates of loss aversion in the literature that assume a linear utility function. Most estimates of the prospect theory utility function report close to a linear utility function, at least for small stakes (Dhami, 2019, Vol. 1). Under a linear utility function, the mean of loss aversion for our data is 1.83. Chapman et al. (2019) report median values of loss aversion between 1.5 and 2.5 in their survey of the literature. For our data, the median value of loss aversion is 1.05 for non-labor income (T1) and 1.17 for labor income (T2). The mean value of loss aversion, under a non-linear utility function, in our data, is 1.37 in T1 (non-labor income) and 1.53 in T2 (labor income).[38] These figures are consistent with our first conjecture about higher loss aversion for labor income (see (2.5)).

Chapman et al. (2019) use data for 2000 US respondents on MTurk to measure loss aversion using a new procedure (DOSE). They find a nearly equal split between *loss averse* ($\lambda > 1$) and *loss tolerant* ($\lambda \leq 1$) individuals. By contrast, a comparison of 8 lab studies shows that loss averse subjects range from 70% to 83% of the total; the rest, 13% to 30%, are loss tolerant.[39]

[37] This excludes eight subjects with loss aversion greater than 10.

[38] The original median estimates of loss aversion from the work of Kahneman and Tversky were around 2.25; see Kahneman and Tversky (2000) for several surveys. Blake et al. (2021) find an average figure of loss aversion of 2.41 for the UK population. A meta analysis by Brown et al. (2023) finds an average value of loss aversion between 1.8 and 2.1.

[39] 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.,

We find that 52% of our student subjects in T1 and 58% in T2 are loss averse. We follow the Chapman et al. (2019) binary distinction between loss averse ($\lambda > 1$) and loss tolerant ($\lambda \leq 1$) subjects, and use it in our econometric analysis in Section 8. This is likely to mitigate measurement errors, and the effect of extreme strategic responses in the lottery choice task. We also show in the supplementary section that our results are robust to having a continuous measure of loss aversion.

Recall that our risk aversion measure was obtained by using lotteries in the gains domains only so as not to confound its measurement with loss aversion.[40] We have the following contingency values. Of the loss averse subjects, 193 are risk averse and 69 are risk loving. Of the loss tolerant subjects, 104 are risk averse and 111 are risk loving. The value of Cramér's V (a measure of association between two categorical variables) is 0.2596, indicating low association between risk aversion and loss aversion, allowing for their simultaneous use in the Tobit regressions in Section 8.

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 penalty rate, θ. The relevant questions are Q1–Q6, with an exogenously fixed probability of detection ($p(D) = a > 0$); the relevant predictions are stated in Proposition 2. An increase in the audit penalty θ is predicted to reduce evasion (Proposition 2b) and an increase in the tax rate t is predicted to increase evasion (Proposition 2c). These results are not new, but they allow us to check that our basic comparative static results are in line with our predictions, and with other findings in the literature.

7.1 The effect of increasing the tax rate

Table 3: The effect of increasing the tax rate (two-tailed paired t-tests) on declared income

Treatment/Declared income		Q1 ($t = 5\%$)	Q2 ($t = 30\%$)	Q3 ($t = 60\%$)	Q1 vs. Q2	Q1 vs. Q3	Q2 vs. Q3
Primed & labor	Mean	73.7	60.7	49.7	0.0001	0.0000	0.0000
	Median	75	50	40	(0.0000)	(0.0000)	(0.0000)
Primed & Non-labor	Mean	65.6	53.3	42.6	0.0000	0.0000	0.0000
	Median	75	50	30	(0.0000)	(0.0000)	(0.0000)
Unprimed & labor	Mean	65.4	48.3	39.3	0.0000	0.0000	0.0001
	Median	75	50	30	(0.0000)	(0.0000)	(0.0000)
Unprimed & Non-labor	Mean	71.5	58.2	45.7	0.0000	0.0000	0.0000
	Median	75	50	40	(0.0000)	(0.0000)	(0.0000)

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

(2004). These references are given in full in the supplementary section but not in the main paper.

[40] Chapman et al. (2019) measure risk aversion through the parameter of the power form of the utility function (the parameter γ in our model; see (2.3)). Whilst this leads to the correct estimates of risk aversion under expected utility theory, it is problematic 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).

Table 3 shows the average of declared incomes across all treatments for Q1–Q3, with respective tax rates $t = 5\%$, 30%, and 60%. We keep fixed the penalty rate ($\theta = 1$) and the audit probability ($p = a = 3\%$, $b = 0$). We find that the declared income goes down with an increase in the tax rate, which is consistent with our model. Thus, there is no Yitzhaki puzzle under prospect theory (Proposition 2c), in line with the evidence, while there is a predicted Yitzhaki puzzle under expected utility theory and under reasonable attitudes to risk. There is a significant fall in the declared income when the tax rate goes up from 5% to 30%; from 5% to 60%; and from 30% to 60% ($p < 0.000$ for all cases). These results are consistent with other empirical results (see the introduction) that report a positive relation between evasion and tax rates.

7.2 The effect of increasing the penalty rate

Table 4: The effect of increasing the fine rate, f (two-tailed paired t-tests) on declared income.

Treatment/Declared income		Q4 ($f = 0$)	Q5 ($f = 1$)	Q6 ($f = 3$)	Q4 vs. Q5	Q4 vs. Q6	Q5 vs. Q6
Primed & labor	Mean	32.5	46.4	73.9	0.0000	0.0000	0.0000
	Median	10	50	75	(0.0000)	(0.0000)	(0.0000)
Primed & Non-labor	Mean	30.1	40.9	63.4	0.0000	0.0000	0.0000
	Median	1	25	68	(0.0000)	(0.0000)	(0.0000)
Unprimed & labor	Mean	26.6	35.5	65.0	0.0000	0.0000	0.0000
	Median	3.5	25	70	(0.0000)	(0.0000)	(0.0000)
Unprimed & Non-labor	Mean	36.0	42.4	65.4	0.0163	0.0000	0.0000
	Median	20	25	71	(0.00413)	(0.0000)	(0.0000)

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

Table 4 compares declared income across treatments as the fine rate $f = 1 + \theta$ is varied from 0, 1, to 3 (or, equivalently, as the penalty rate θ is varied from -1, 0, to 2). We keep fixed the tax rate ($t = 30\%$) and the audit probability ($p = a = 3\%$, $b = 0$). Even when $\theta = -1$, i.e., there is a 100% subsidy to tax evasion, on average, 35% of the income is declared for tax purposes.[41] This is consistent with the presence of moral costs of tax evasion.

In pairwise comparisons of the declared incomes for Q4, Q5, and Q6, there is a significant increase in the declared incomes when the fine rate increases from 0 to 1, and 3 ($p < 0.02$ for all pairwise comparisons). The observed positive association between the fine rate and declared income across all treatments is consistent with our theoretical prediction (Proposition 2b).

8 Regression analysis of the determinants of declared income

Table 6 gives the results of the Tobit regression analysis with robust standard errors for data that is pooled across all questions.[42] Since we have 5 different levels of incomes, and taxpay-

[41]The median of 1 here arises due to the large number of taxpayers who choose to declare nothing.

[42]Our analysis is robust to other model specification suitable for corner solutions. For example, we used different levels of evasion in an ordered probit model and the results are qualitatively the same. Table 4 in the

ers make their declaration decision based on their level of income, we use the proportion of declared income, $Z = D/W$, as our dependent variable; in this section we shall refer to it as simply "declared income" instead of the longer "proportion of declared income".[43] The relevant predictions are summarized in Proposition 1 and Proposition 2. We run a Tobit regression of the form

$$Z = \beta X + u, \tag{8.1}$$

where u is normally distributed with mean zero and variance normalized to unity; X is a vector of explanatory variables and β is a vector of coefficients. The explanatory variables used in (8.1), with the corresponding names given in Table 6, and the basic data on the individual categories, are as follows.

• d_λ, or 'Loss aversion': Dummy variable that takes the value 1 if the subject is loss averse ($\lambda > 1$) and 0 if the subject is loss tolerant ($\lambda \leq 1$). This classification follows Chapman et al., (2019); see the discussion in Section 6.2. However, we demonstrate the robustness of our results to a continuous measure of loss aversion in the supplementary section.

• d_R, or 'Risk aversion': Dummy variable that captures attitudes to risk. It takes the value 1 for risk averse individuals and 0 for risk loving individuals.[44]

• d_T, or 'Labor' : Treatment dummy that equals 0 for treatment T1 (non-labor income) and 1 for treatment T2 (labor income).

• d_P, or 'Prime': Treatment dummy that equals 0 for unprimed and 1 for the primed group.

Table 5 gives the data on the different categories of the dummy variables listed above. We have a fairly even distribution across the relevant categories.

Table 5: Brief description of the data corresponding to the treatment/behavioral dummies

Dummy variable	0	1
Labor, d_T	231 (48%)	246 (52%)
Prime, d_P	236 (49%)	241 (51%)
Loss aversion, d_λ	215 (45%)	262 (55%)
Risk aversion, d_R	180 (38%)	297 (62%)

• Probability of detection: Dummy variable that equals to 1 for endogenous audit probability ($p = a - bD$, $a, b > 0$); and 0 when there is an exogenous probability of detection ($p = a$; $a > 0$, $b = 0$).

• We also use the interaction terms: $d_\lambda d_T$, $d_\lambda d_R$, $d_R d_T$, $d_\lambda d_R d_T$. The names of the interaction terms are self explanatory, e.g., $d_\lambda d_T$ is named Loss aversion:Labor and $d_\lambda d_R$ is named Loss aversion:Risk aversion.

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

supplementary section reports the results.

[43]In the supplementary file we examine the robustness of our results to using OLS with 'declared income' as the dependent variable. Table 4 reports the results. Our findings are qualitatively unchanged.

[44]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. Furthermore, since we check risk aversion by a direct comparison of certainty equivalent with the expected value, this must necessarily be a dummy variable.

• 'Age' gives the self-reported age of subjects. The minimum age is 18, the maximum is 37, mean age is 21.6, median is 20, and the standard deviation is 2.80.

• 'Gender' is a dummy for gender and takes the value 1 for female and 0 for male. 245/477 subjects (51%) are males and 232/477 subjects (49%) are females (there are 7/477 transgenders/others that are classified as females in the regression).

• 'Marital' is a dummy for marital status and takes the value 0 for single and 1 otherwise. Since our sample consists of students, most are single 464/477 (97%). 7 subjects are married, 2 subjects are in a domestic relationship, and 4 have indicated 'other' for their marital status.

• 'Religion' is a dummy for religion. It equals 1 for Hindu subjects and 0 otherwise. The majority of our sample is Hindus 335/477 (70%) (Hindus are approximately 80% of the Indian population). Others in the sample subscribe to Islam (4%), Christianity (3%), Jainism (4%), Sikhism (0.8%), Atheism (11%), something else (1.8%), and the rest choose "I don't want to say it" as their religion (6%).

• 'Education' is a dummy variable. It equals 1 for Masters/PhD students, and 0 otherwise. 221/477 subjects (46%) are graduate students, and 256/477 subjects (54%) are undergraduates.

In the supplementary section, we successfully demonstrate the robustness of our results to the following extensions. (1) Measurement of the loss aversion parameter on a continuous scale. (2) Different parameters for the probability weighting function used to estimate loss aversion. (3) Adding income on the RHS of (8.1).

In Table 6, we describe 3 successively more complex econometric models. In Model 1, we only include the deterrence parameters, loss aversion, risk aversion, and the treatment dummies (Labor and Prime) as the explanatory variables. None of the treatment dummies are significant at 5%. In Model 2, we add several individual-specific covariates, such as time, age, gender, marital, education, and religion. In our most general specification, in Model 3, we also include the interaction terms between various dummy variables (these are $d_\lambda d_T$, $d_\lambda d_R$, $d_R d_T$, and $d_\lambda d_R d_T$). None of the signs of the regressors changes as we successively include new variables, although their magnitudes and sometimes their significance levels may change. Below, we report on the results from our most complete model, Model 3.[45]

We first verify two effects that we have already demonstrated in Section 7 above, and are predicted by our model (Proposition 1 and Proposition 2). An increase in the tax rate reduces declared income, which is consistent with prospect theory, but not with expected utility theory (Yitzhaki puzzle). An increase in the fine rate increases declare income. Both are statistically significant at 1%.

Recall our discussion about ambiguous treatment effects predicted by economic theory, hence, the treatment effect effect is an empirical question. We find that taxpayers declare 5 percentage point more labor income relative to non-labor income. Thus, overall and in terms of the direct effect, loss aversion dominates morality costs in inducing greater declaration of labor income. Taxpayers declare, on average, 6.7 percentage point more of their income when there is an endogenous probability of detection (that depends on the amount declared) relative

[45]We also ran Tobit regressions without the variable 'marital' with income dummies and with continuous measure of loss aversion as robustness checks and the qualitative results are unchanged. These are reported in Table 2 of the supplementary section.

Table 6: Tobit regression results

	Dependent variable:		
	Proportion of declared income		
	(1)	(2)	(3)
Tax rate	−1.035***	−1.030***	−1.030***
	(0.083)	(0.082)	(0.082)
Fine rate	0.290***	0.290***	0.290***
	(0.017)	(0.016)	(0.016)
Probability of detection	0.058*	0.065*	0.067*
	(0.035)	(0.034)	(0.034)
Loss aversion	0.052**	0.028	0.180***
	(0.026)	(0.025)	(0.059)
Risk aversion	−0.070***	−0.044*	−0.017
	(0.027)	(0.026)	(0.051)
Labor	0.0003	0.022	0.050
	(0.025)	(0.025)	(0.051)
Prime	0.039	0.056**	0.053**
	(0.025)	(0.025)	(0.025)
Time		−0.005***	−0.005***
		(0.001)	(0.001)
Age		0.045***	0.046***
		(0.006)	(0.006)
Gender		0.209***	0.212***
		(0.026)	(0.026)
Marital		0.202**	0.195**
		(0.087)	(0.087)
Education		−0.119***	−0.121***
		(0.032)	(0.032)
Religion		0.086***	0.096***
		(0.028)	(0.028)
Loss aversion:Risk aversion			−0.192**
			(0.075)
Loss aversion:Labor			−0.242***
			(0.082)
Risk aversion:Labor			−0.015
			(0.071)
Loss aversion:Risk aversion:Labor			0.283***
			(0.105)
logSigma	−0.398***	−0.425***	−0.428***
	(0.021)	(0.021)	(0.021)
Constant	0.540***	−0.366***	−0.420***
	(0.050)	(0.132)	(0.137)
	3339	3339	3339

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are in parentheses.

to an exogenous probability of detection. Several control variables such as time, age, gender, marital status, religion, and education are significant. Those who spend more time deliberating on the declaration decision, declare lower income, but the effect is small. Those who are older declare more; a unit increase in age (measured in years) increases declared income by 4 percentage point. Females declare 21.2 percentage point more income relative to males. This ties in with the literature on gender differences in economic decisions including the greater tendency of males to be more overconfident and take more risks (Dhami, 2016); we extend these results to illegal activity.

Married taxpayers declare 19.1 percentage point higher income than those who are unmarried. The more educated students declare less income; Masters/PhD students reduce declared income by 12.1 percentage point, relative to others with lower educational qualifications. This is an interesting result and deserving of greater exploration in future research. Primed subjects declare 5.3 percentage point more income relative to unprimed subjects.[46] Those who give their religion as 'Hindu,' declare 9.6 percentage point more income relative to those who do not.[47]

Loss aversion, on its own, is highly significant and increases declared incomes. In terms of the direct effect, those who are loss averse declare 18.0 percentage point more of their income, relative to those who are loss seeking. This finding is consistent with our theory and our proposed transmission mechanism behind mental accounting, based on loss aversion. We provide the first direct empirical evidence, using subject-specific, directly measured, loss aversion, for the underlying transmission channel in most 'prospect theory based' explanations of tax evasion (Bernasconi, 1998; Yaniv, 1999; Bernasconi and Zanardi, 2004; Dhami and al-Nowaihi, 2007, 2010; Eide et al., 2011; Alm and Torgler, 2012; Engström et al., 2015; Rees-Jones, 2018). Risk aversion, by itself, is not significant and the magnitude of the effect on declared incomes is small at 1.7 percentage point. But it has an important role to play through its interaction effects with other variables, as we show below. The following two interaction terms that involve the treatment dummy are significant, Loss aversion:Labor ($d_\lambda d_T$) and Loss aversion:Risk aversion:Labor ($d_\lambda d_R d_T$). If the taxpayer treated both sources of income in an identical manner, which would be the case if mental accounting were absent, then we should not have obtained statistical significance for these variables. Since the determinants of tax evasion are dependent on the source of income, this supports a mental accounting based explanation of tax evasion that we are interested in. However, our analysis of mental accounting goes beyond just identifying source-dependent evasion. We highlight the main channels, loss aversion and risk aversion, through which mental accounting works, and empirically verify it.

We now use Table 6 to identify several effects arising from the interaction of the dummy variables in our model. We use the notation $E(Z \mid d_T, d_\lambda, d_R)$ to denote the average declared income, conditional on different values of the three conditioning dummy variables, d_T, d_λ, d_R.[48]

[46] As noted in Section 5, our priming information is factual but fairly extreme and flags up widespread evasion with potentially serious consequences for public services. Hence, subjects react by slightly increasing declared income in the primed group. It is conceivable that with a different prime, we might not get this result. However, our main interest is not in the behavior of the primed versus unprimed group.

[47] For a recent analysis of the effects of religious identity on important economic decisions using Indian data, see Dhami et al. (2022).

[48] All relevant marginal effects are reported in Table 5 of the supplementary section. Here, we only focus on

The main result of interest, from a treatment effect point of view, is the average differences in the declared amounts of loss averse subjects ($d_\lambda = 1$) as we vary the two sources of incomes, labor income ($d_T = 1$) and non-labor income ($d_T = 0$). However, we also condition on risk attitudes: risk averse ($d_R = 1$) and risk loving ($d_R = 0$).

1. Loss averse taxpayers, $d_\lambda = 1$, who are risk averse, $d_R = 1$.

$$E(Z \mid d_T = 1, d_\lambda = 1, d_R = 1) - E(Z \mid d_T = 0, d_\lambda = 1, d_R = 1) = 0.076. \tag{8.2}$$

   From (8.2), restricting attention to loss averse ($d_\lambda = 1$) and risk averse ($d_R = 1$) taxpayers, subjects declare 7.6 percentage point more income when they earn labor income ($d_T = 1$) relative to non-labor income ($d_T = 0$). This effect, in conjunction with our earlier finding in Section 6.2 on higher average loss aversion for labor income, is consistent with our main assumption on the transmission channel based on loss aversion.

2. Loss averse taxpayers, $d_\lambda = 1$, who are risk loving, $d_R = 0$.

$$E(Z \mid d_T = 1, d_\lambda = 1, d_R = 0) - E(Z \mid d_T = 0, d_\lambda = 1, d_R = 0) = -0.192. \tag{8.3}$$

   From (8.3), loss averse subjects, who are also risk loving, declare 19.2 percentage point less of their labor incomes as compared to their non-labor incomes. Comparing (8.2) and (8.3), risk aversion *strengthens* the cautionary effect of loss aversion, while risk loving behavior *attenuates*, and even *reverses* the effect of loss aversion. As far as we are aware, this is the first demonstration of such a result in the literature on decision making under risk and uncertainty, based on directly measured subject-specific loss aversion and risk aversion.

   The results in (8.2) and (8.3), since they directly reveal evasion differences for two different sources of income, that are identical in all other respects, support our claims on source-dependent mental accounting in this paper. A similar comment applies to the results below.

3. Loss seeking taxpayers, $d_\lambda = 0$, who are risk averse, $d_R = 1$.

$$E(Z \mid d_T = 1, d_\lambda = 0, d_R = 1) - E(Z \mid d_T = 0, d_\lambda = 0, d_R = 1) = 0.035. \tag{8.4}$$

   From (8.4), restricting attention to loss seeking ($d_\lambda = 0$) and risk averse ($d_R = 1$) taxpayers, subjects declare 3.5 percentage point more income when they earn labor income ($d_T = 1$) relative to non-labor income ($d_T = 0$). Comparing with the case of loss averse subjects in (8.2), loss seeking subjects declare lower incomes. This is consistent with our predictions. In this case, the cautionary effects of risk aversion counter the opposing effect of loss seeking behavior.

4. Loss seeking taxpayers, $d_\lambda = 0$, who are risk loving, $d_R = 0$.

$$E(Z \mid d_T = 1, d_\lambda = 0, d_R = 0) - E(Z \mid d_T = 0, d_\lambda = 0, d_R = 0) = 0.050. \tag{8.5}$$

special cases of interest.

From (8.5), restricting attention to loss seeking ($d_\lambda = 0$) and risk loving ($d_R = 0$) taxpayers, subjects declare 5.0 percentage point more income when they earn labor income ($d_T = 1$) relative to non-labor income ($d_T = 0$). The comparison between (8.3) and (8.5) is interesting and difficult to reconcile with known theory. Loss aversion interacts with risk loving behavior to produce lower declared labor incomes relative to non-labor incomes in (8.3); we have conjectured the reasons, above. However, loss seeking interacts with risk seeking to produce relatively higher declared labor incomes in (8.5). It would appear that the interaction between loss aversion, risk aversion, and mental accounting of incomes is complex and requires new further developments.

Other treatment comparisons are also possible. We give two such comparisons below. The relevant calculations are given in the supplementary section.

1. Consider risk averse taxpayers, $d_R = 1$. (i) For labor income, $d_T = 1$, the average additional amount declared by loss averse subjects relative to loss seeking subjects, is 2.9 percentage point. This is consistent with our theory. (ii) For non-labor income, an identical comparison gives a figure of -1.2 percentage point, which is hard to explain with our theory, but the effect is smaller.

2. Consider risk loving taxpayers, $d_R = 0$. In this case, the evidence considered above suggests that risk loving behavior may or may not reverse the effects of loss aversion, depending on the source of income, which is a new finding. Hence, it is difficult to predict a-priori which effect will dominate, thus, the answer has to be entirely empirical, although either way it indicates the presence of mental accounting. (i) For labor income $d_T = 1$ the average additional amount declared by loss averse subjects relative to loss seeking subjects, is -6.2 percentage point. (ii) For non-labor income, an identical comparison gives a figure of 18.0 percentage point higher declared income.

9 Conclusions

Our main contribution is to provide the first rigorous demonstration of the link between subject specific loss aversion and tax evasion, which lies at the heart of the modern theories of tax evasion.

There are several novel features of our analysis. First, we derive theoretical predictions for tax evasion by exploiting the link between loss aversion, risk aversion, mental accounting, and moral costs in a prospect theory framework. Second, we propose a theoretical framework for measuring subject-specific loss aversion; and empirically determine a strategy to measure it that is independent of risk aversion. Third, a combination of loss aversion, moral costs, and risk aversion are essential for an understanding of tax evasion that depends on the source of income. For instance, it appears that risk aversion strengthens the cautionary effect of loss aversion, while risk loving behavior attenuates the effect of loss aversion. However, a third dimension, the source of income, makes it difficult to present truly generalized findings. Fourth, our empirical results show that entitlements to income influence the degree of evasion (source-dependent evasion). Fifth, we show that the effectiveness of loss aversion in reducing evasion is income-source specific. The interactions of the treatment effect with loss/risk attitudes are significant. These findings suggest the importance of mental accounting. Sixth, we confirm the predicted comparative static effects of the probability of detection, the penalty rate and the tax rate on tax evasion for the same set of subjects, for two different sources of income.

While we are able to explain most of our results, our model is unable to provide answers to some of the results. This is the case with our finding of new and unknown interaction effects of risk aversion with loss aversion that are income source dependent. This requires further developments in the relevant theory.

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1 Supplementary Sections

The supplementary section gives the complete version of our theoretical model and extra empirical results. We also demonstrate the robustness of our results to alternative modeling assumptions. In order to ensure that this section can be read independently, there is an unavoidable overlap with the presentation of the theoretical model in the body of the paper.

1.1 Basic setup

There are N taxpayers in society, and there is an underlying distribution, F, of n discrete taxable income levels, $0 = W^1 < W^2 < ... < W^n$, such that for income level W^k, there are n_k taxpayers, $k = 1, ..., n_k$. Hence, the relative frequency of taxpayers with income W^k is n_k/N. The tax authorities have beliefs about F, but do not observe individual incomes (or they observe them with error), allowing for the possibility of tax evasion. The Allingham-Sandmo-Yitzhaki framework considers the tax evasion decision of a single taxpayer, whose income is unknown to the tax authorities, conditional on the endogenously given deterrence parameters. Suppose that we pick out an individual randomly from the distribution F and (unknown to the tax authorities), this individual has income W^k. We are interested in the tax evasion decision of this particular individual. Since the income of the individual is unknown to the tax authorities, to reduce notation we simply write the taxable, and unobserved, income of the chosen individual as W. Henceforth, we speak of this individual as 'the taxpayer'.[49]

[49] We have no further use for the distribution F. In other problems, e.g., the determination of the optimal tax/enforcement parameters, the distribution F plays a critical role.

We distinguish between the source of the taxable income, i.e., either *labor income*, L, or *non-labor income* , N. So we may write the income of the taxpayer from source $j = L, N$ as W_j. In our experiments, the taxpayer either has labor income ($j = L$) or non-labor income ($j = N$), but never both. Hence, we may conserve notation further and dispense entirely with the subscript j (except in inequalities (1.11) and (1.12) below) and refer to the taxpayer as having unobserved, taxable, income W.

Each source of income is taxed at the identical constant marginal rate t, $0 < t < 1$. The taxpayer chooses to declare income $D \in [0, W]$ and evades the amount $W - D$. The two deterrence parameters, audit probability and penality rate, are identical for the two sources of incomes. Irrespective of the source of income, the declaration decision of the taxpayer is audited with probability $p(D) \in [0, 1]$ such that

$$p(D) = a - bD; a \in [0, 1], 0 \leq b \leq \frac{a}{W}. \tag{1.1}$$

From (1.1), greater declaration of income reduces the audit probability. The restrictions on a, b ensure that $p(D) \in [0, 1]$. 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 $t(W - D)$, and a penalty $\theta t(W - D)$, where θ is the *penalty rate* on evaded taxes. Thus, if caught, the taxpayer pays the following amount to the tax authorities

$$t(1 + \theta)(W - D) \equiv ft(W - D), \text{ where } f = 1 + \theta. \tag{1.2}$$

We call f the *fine rate*. A taxpayer who evades taxes, faces morality costs $c \in [\underline{c}, \bar{c}]$ in monetary units per unit of evaded taxes, *irrespective of whether 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

$$\bar{c} \leq t. \tag{1.3}$$

Condition (1.3) is purely technical, and as we show below, it ensures that the objective function is real-valued and not an imaginary number.[50]

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). Using the discussion above, the state-contingent income Y^s of the taxpayer is:

$$Y^{NC} = W - tD - c(W - D). \tag{1.4}$$

$$Y^C = (1 - t)W - \theta t(W - D) - c(W - D). \tag{1.5}$$

1.2 Prospect theory value function

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

[50]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; Slemrod 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.

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) provides a useful, and empirically satisfactory, reference point and enhances the status-quo in applications (Dhami and al-Nowaihi, 2007, 2010).[51] For this reason, we define the reference income, R, of the taxpayer to be the legal after-tax income

$$R = (1 - t)W. \tag{1.6}$$

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 2 below. Denote the state-contingent income relative to the reference point by $X^s = Y^s - R$, $s = C,\ NC$, where Y^s is defined in (1.4), (1.5). Using (1.4), (1.5), (1.6), and recalling that $0 \leq D \leq W$, we get for all D:

$$X^{NC} = (t - c)(W - D) \geq 0 \tag{1.7}$$

$$X^C = -(\theta t + c)(W - D) < 0. \tag{1.8}$$

Remark 2 *: 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 (1.6)), then prospect theory reduces to rank dependent utility. But Eide et al. (2011) showed 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 (1.6) (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, we have $X^{NC} \geq 0$ and $X^C < 0$; this was shown formally in Dhami and al-Nowaihi (2007, 2010).*

The taxpayer faces the following *lottery in incremental form* under prospect theory[52]

$$L = (X^C, p; X^{NC}, 1 - p). \tag{1.9}$$

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):

$$v(X^s) = \begin{cases} (X^s)^\gamma & if \quad X^s \geq 0 \\ -\lambda(-X^s)^\gamma & if \quad X^s < 0 \end{cases} ; s = C, NC, \tag{1.10}$$

[51] 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 there is evidence of expectations-based reference points; see Dhami (2019, Vol. 1, Section 2.8.3).

[52] 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).

where $\gamma \geq 0$ (power form parameter) and $\lambda > 0$ (loss aversion parameter) are preference parameters that we estimate for each subject in our study; the evidence indicates that the median values are $\gamma_{med} \approxeq 0.88$, $\lambda_{med} \approxeq 2.25$ (Dhami, 2019, Volume 1).[53] Following Chapman et al. (2019), a taxpayer is *loss averse* if $\lambda > 1$ and *loss tolerant* if $\lambda \leq 1$.

The introduction to the paper discussed evidence that earned labor income creates greater entitlements relative to unearned non-labor income through differences in loss aversion and moral costs of evasion. To formally state this hypotheses, we temporarily invoke the subscript $j = L, N$ that was suppressed above. Let c_j, λ_j denote, respectively, moral cost of evasion and loss aversion for the taxpayer from income source $j = L, N$. Then, the taxpayer exhibits relatively lower moral cost of evading labor income.

$$c_L < c_N, \tag{1.11}$$

and relatively higher loss aversion from labor income.

$$\lambda_N < \lambda_L. \tag{1.12}$$

Notation Suppressing a taxpayer-specific index, $i = 1, 2, ...N$, and the index $j = L, N$ for the income source is pedagogically preferable. However, we do allow for individual-specific and income source-specific preference parameters; indeed, such heterogeneity is a common finding in all experiments. We could have written the preference parameters, utility function parameter, morality cost and loss aversion in full notation as, respectively, $\gamma_{ij}, c_{ij}, \lambda_{ij}$. The corresponding full notation for the declared income, reference income, and the income relative to the reference point in state $s = C, NC$ is, respectively, D_{ij}, R_{ij}, X_{ij}^s.

Non-linear probability weighting is an important feature of prospect theory. However, we shall assume linear probabilities in our main model.[54] Since there is one outcome each in the domain of gains and losses (see (1.7), (1.8)), the prospect theory utility of the lottery L in (1.9) is

$$V = (1 - p(D))v(X^{NC}) + p(D)v(X^C). \tag{1.13}$$

where X^C, X^{NC} are defined in (1.7), (1.8) and v in (1.10).

Define the vector of policy and preference parameters for any taxpayer by

$$\phi = (\theta, t, a, b, \gamma, c, \lambda). \tag{1.14}$$

1.3 The optimization problem and results

Substituting (1.7), (1.8), (1.10) in (1.13), we get the optimization problem of the taxpayer:

$$D^* \in \underset{<D \in [0,W]>}{\arg\max}\ V(D, \phi) = (W - D)^\gamma [(1 - p(D))(t - c)^\gamma - p(D)\lambda(\theta t + c)^\gamma], \tag{1.15}$$

[53] 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).

[54] 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).

where $\phi = (\theta, t, a, b, \gamma, c, \lambda)$ is given in (1.14).[55] From (1.15), and using (1.1) to get $p'(D) = -b$, we have

$$\frac{\partial V}{\partial D} = (t-c)^\gamma[-(1-p(D))\gamma(W-D)^{\gamma-1} + b(W-D)^\gamma] - \lambda(\theta t + c)^\gamma[-p(D)\gamma(W-D)^{\gamma-1} - b(W-D)^\gamma]. \quad (1.16)$$

Proposition 3 *(a) A solution $D^*(\phi) \in [0, W]$ to the problem in (1.15) 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 (1.14), the sign of $\frac{\partial D^*}{\partial z}$ is that of $\frac{\partial^2 V}{\partial D \partial z}$.

Proof of Proposition 3: (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 (1.15) as

$$V(D, \phi) = (W-D)^\gamma[(t-c)^\gamma - Ap(D)], \quad (1.17)$$

where

$$A = [(t-c)^\gamma + \lambda(\theta t + c)^\gamma] > 0. \quad (1.18)$$

If the optimal choice $D^* = W$, then from the objective function in (1.15), $V(W, \phi) = 0$. Hence, if there is an interior solution $D^* \in (0, W)$ it must be that $V(D^*, \phi) \geq 0$. It follows from (1.17) and (1.18) that for $D^* \in (0, W)$,

$$(t-c)^\gamma - Ap(D) \geq 0. \quad (1.19)$$

We can write (1.16) as

$$\frac{\partial V}{\partial D} = -[(t-c)^\gamma - Ap(D)]\gamma(W-D)^{\gamma-1} + (W-D)^\gamma bA. \quad (1.20)$$

At an interior solution $\frac{\partial V}{\partial D} = 0$. Using (1.20) this implies that

$$bA = [(t-c)^\gamma - Ap(D)]\gamma(W-D)^{-1}. \quad (1.21)$$

Differentiating $\frac{\partial V}{\partial D}$ with respect to D, and substituting bA from (1.21), we get

$$\frac{\partial^2 V}{\partial D^2} = -\gamma bA(W-D)^{\gamma-1} - \gamma(W-D)^{\gamma-2}[(t-c)^\gamma - Ap(D)]. \quad (1.22)$$

From (1.19), 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 $D^* \in (0, W)$,

$$\frac{\partial D^*}{\partial z} = -\frac{\partial^2 V}{\partial D \partial z} \Big/ \frac{\partial^2 V}{\partial D^2}; z = \theta, t, a, b, \gamma, c, \lambda. \quad (1.23)$$

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

Proposition 3a shows that we can proceed with a formal analysis of the comparative static effects. Proposition 3b gives an intermediate result that simplifies the derivation of comparative static results.

[55] The term $(t-c)^\gamma$ in (1.15) shows why the technical assumption in (1.3), $\bar{c} \leq t$, was necessary to ensure that the objective function is real valued.

1.4 Comparative Statics

Recall from (1.1) that the probability of detection is $p(D) = a - bD$; $a, b \geq 0$. Propositions 4 and 5 below give the comparative static results for the case $b > 0$ (i.e., the probability of detection is decreasing in the amount declared). We then provide a discussion of the results. In Section 1.5 and Proposition 6 we separately discuss the case of an exogenous probability of detection, i.e., $b = 0$.

Proposition 4 *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., $\frac{\partial D^*}{\partial a} > 0$.[56]
(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., $\frac{\partial D^*}{\partial c} > 0$.

Proof of Proposition 4: Using Proposition 3(b), we now sequentially determine the signs of the derivatives in (1.23).

(a) Implicitly differentiating the first order condition (1.16), we get

$$\frac{\partial^2 V}{\partial D \partial \theta} = \lambda \gamma t (\theta t + c)^{\gamma - 1} [p(D) \gamma (W - D)^{\gamma - 1} + b(W - D)^{\gamma}] > 0. \tag{1.24}$$

Using Proposition 3b and (1.24), 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 (1.16), we get

$$\frac{\partial^2 V}{\partial D \partial a} = \gamma (W - D)^{\gamma - 1} [(t - c)^{\gamma} + \lambda (\theta t + c)^{\gamma}] > 0. \tag{1.25}$$

Using Proposition 3b and (1.25), we get that $\frac{\partial D^*}{\partial a} > 0$.

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

Implicitly differentiating the first order condition (1.16)

$$\frac{\partial^2 V}{\partial D \partial \lambda} = -(\theta t + c)^{\gamma} [-p(D) \gamma (W - D)^{\gamma - 1} - b(W - D)^{\gamma}] > 0. \tag{1.26}$$

Using Proposition 3b, and (1.26), it follows that $\frac{\partial D^*}{\partial \lambda} > 0$.

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

Implicitly differentiating the first order condition (1.16), we get

$$\begin{aligned} \frac{\partial^2 V}{\partial D \partial t} &= \gamma (t - c)^{\gamma - 1} [-(1 - p(D)) \gamma (W - D)^{\gamma - 1} + b(W - D)^{\gamma}] \\ &\quad - \lambda \gamma \theta (\theta t + c)^{\gamma - 1} [-p(D) \gamma (W - D)^{\gamma - 1} - b(W - D)^{\gamma}]. \end{aligned} \tag{1.27}$$

[56] 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.

Define

$$P = p(D)\gamma(W - D)^{\gamma-1} + b(W - D)^{\gamma} > 0. \tag{1.28}$$

Using (1.28), the first order condition for an interior optimum, $\frac{\partial V}{\partial D} = 0$ in (1.16) can be written as

$$(t - c)^{\gamma}[-\gamma(W - D)^{\gamma-1} + P] = -P\lambda(\theta t + c)^{\gamma}. \tag{1.29}$$

Using (1.28), (1.27) can be rewritten as

$$\frac{\partial^2 V}{\partial D \partial t} = \gamma(t - c)^{\gamma-1}[-\gamma(W - D)^{\gamma-1} + P] + P\lambda\gamma\theta(\theta t + c)^{\gamma-1}. \tag{1.30}$$

Substitute (1.29) in (1.30)

$$\frac{\partial^2 V}{\partial D \partial t} = -c(1 + \theta)\frac{P\gamma\lambda(\theta t + c)^{\gamma}}{(t - c)(\theta t + c)} < 0. \tag{1.31}$$

It follows from Proposition 3b, (1.28), and (1.31) that $\frac{\partial D^*}{\partial t} < 0$.

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

The first order condition (1.16) for an interior optimum can be written as:

$$\frac{\partial V}{\partial D} = (t - c)^{\gamma} Z_1 + \lambda(\theta t + c)^{\gamma} Z_2 = 0 \tag{1.32}$$

where $Z_1 = [-(1-p(D))\gamma(W-D)^{\gamma-1}+b(W-D)^{\gamma}]$ and $Z_2 = [p(D)\gamma(W-D)^{\gamma-1}+b(W-D)^{\gamma}] > 0$ 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

$$\frac{\partial^2 V}{\partial D \partial c} = -\gamma(t - c)^{\gamma-1} Z_1 + \lambda\gamma(\theta t + c)^{\gamma-1} Z_2 > 0. \tag{1.33}$$

Using Proposition 3b and (1.33), we have that $\frac{\partial D^*}{\partial c} > 0$. ■

Discussion of the results: From Proposition 4a, 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 $s = C$, also reducing the marginal returns from evasion, which reduces evasion. 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 4b). From Proposition 4c, 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 and moral costs of evasion.[57] Finally, an increase in the moral cost, c, of tax evasion reduces evasion (Proposition 4d). An increase in c reduces each of X^{NC} and X^{C}, reducing the marginal utility from not declaring income in both states. Hence, optimal evasion falls.

Recall from (1.11) and (1.12) our hypotheses that for earned labor income, loss aversion is relatively higher ($\lambda_N < \lambda_L$) and moral costs of evasion are relatively lower ($c_L < c_N$). From

[57]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).

Proposition 4b an increase in loss aversion reduces evasion and from Proposition 4d, a decrease in moral costs increases evasion. Since these effects oppose each other, depending on the relative strengths of the two effects, the treatment effect (relative evasion in the two treatments) can be positive, zero, or negative.

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

Proposition 5 *(a) There is a critical value of the morality cost, $\hat{c}(\phi)$, such that the global maximum is $D^* = W$ if $\hat{c}(\phi) \leq c$.*
(b) Let $\hat{a} = \left(1 + \frac{\lambda(\theta t + c)^\gamma}{(t-c)^\gamma}\right)^{-1} - \frac{1}{\gamma}bW$ and $b > 0$. Then, for $D \in [0, W)$, $D^* = 0$ is optimal if $\hat{a} > 0$ and the exogenous probability of detection, a, is low enough in the sense that $a < \hat{a}$.
(c) 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.

Proof of Proposition 5: (a) From the proof of Proposition 3, we know that for the case $D^* = W$, we have $V(W, \phi) = 0$. For $D^* = W$ to be the global maximum, we must have $V(D, \phi) \leq 0$ for all $D^* \in [0, W)$. Using (1.17), we have that

$$V(D, \phi) \leq 0 \Longleftrightarrow t\left[\frac{1 - B\theta}{1 + B}\right] \leq c;\ B = \left(\frac{\lambda}{p(D)^{-1} - 1}\right)^{1/\gamma}. \tag{1.34}$$

We have that B is increasing in $p(D)$ and the term $\frac{1-B\theta}{1+B}$ is decreasing in B. The audit probability $p(D) = a - bD$ is decreasing in D and its greatest lowest bound in the interval $D \in [0, W)$ is given by $a - bW$. Hence, a sufficient condition for the inequality in (1.34) to hold is $t\left[\frac{1-B\theta}{1+B}\right] \equiv \hat{c}(\phi) \leq c$, when B is evaluated at $D = W$.

(b) Evaluating $\frac{\partial V}{\partial D}$ in (1.20) at $D = 0$ we get

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

where $A = [(t-c)^\gamma + \lambda(\theta t + c)^\gamma] > 0$ is defined in (1.18). It follows that $\frac{\partial V}{\partial D}\mid_{D=0} < 0$ if

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

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

(c) 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 reduces 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. ■

From Proposition 5a, if the moral costs of evasion are high enough (in the sense that they are bounded below by $\hat{c}(\phi)$), then it is optimal to fully declare all income ($D^* = W$). Proposition 5b deals with the other corner solution $D^* = 0$. This result can be stated in many different ways by placing an upper bound on different exogenous variables. Proposition 5b states the result in terms of an upper bound on the exogenous probability of detection, a. If a is low enough ($a < \hat{a}$ and $\hat{a} > 0$), then there is insufficient deterrence to prevent the taxpayer from evading all income. Proposition 5a gives the comparative static results at the corner solutions.

Proposition 4 above considered the case $p(D) = a - bD$, $b > 0$. Now suppose that $b = 0$, so that $p(D) = a \in [0,1]$ is independent of D. With an exogenous detection probability, we get corner solutions; we show this below.

1.5 Results with an exogenous probability of detection

Substitute $p(D) = a$ in (1.15) to get

$$D^* \in \underset{<D \in [0,W]>}{\arg\max}\ V(D,\phi) = (W-D)^\gamma h(\phi), \tag{1.35}$$

where $h(\phi)$ is given in (1.14) and

$$h(\phi) = [(1-a)(t-c)^\gamma - a\lambda(\theta t + c)^\gamma]. \tag{1.36}$$

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:

$$D^* = \begin{cases} W & if \quad h(\phi) < 0 \\ [0,W] & if \quad h(\phi) = 0 \\ 0 & if \quad h(\phi) > 0 \end{cases}. \tag{1.37}$$

The comparative static properties are similar to those in Proposition 4 for the case $b > 0$, except that they take the form of threshold values that depend on the vector of parameters ϕ, as shown in the next proposition.

Proposition 6 *: 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 $a = a_c(\phi) > 0$ such that if $a < a_c(\phi)$, $D^* = 0$, and if $a > a_c(\phi)$, $D^* = W$. When $a = a_c(\phi)$, we have $D^* \in [0,W]$.
(b) (Penalty rate, θ) Let $\theta \in [0,\bar{\theta}]$, where $\bar{\theta}$ is the maximum possible penalty rate. Then there exists a critical value of $\theta = \theta_c(\phi) > 0$ such that when $\theta < \theta_c(\phi)$, $D^* = 0$, and when $\theta > \theta_c(\phi)$, $D^* = W$. When $\theta = \theta_c(\phi)$, we have $D^* \in [0,W]$.
(c) (Tax rate, t) There exists a critical value of the tax rate $t_c(\phi) > 0$ such that for all $t < t_c(\phi)$, $D^* = W$, and for $t > t_c(\phi)$, $D^* = 0$. When $t = t_c(\phi)$, we have $D^* \in [0,W]$.
(d) (Loss aversion, λ) There exists a critical value of the parameter of loss aversion $\lambda_c(\phi) > 0$ such that if $\lambda < \lambda_c(\phi)$, then $D^* = 0$, and if $\lambda > \lambda_c(\phi)$, then $D^* = W$. When $\lambda = \lambda_c(\phi)$, we have $D^* \in [0,W]$.

Proof of Proposition 6: From (1.36), 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 $\frac{\partial h}{\partial a} = -(t-c)^\gamma - \lambda(\theta t + c)^\gamma < 0$. Furthermore: (i) $h\mid_{a=0} = (t-c)^\gamma > 0$, and (ii) $h\mid_{a=1} = -\lambda(\theta t + c)^\gamma < 0$. Hence, there exists a critical value $a = a_c(\phi) = \frac{(t-c)^\gamma}{(t-c)^\gamma + \lambda(\theta t + c)^\gamma}$ for which $h\mid_{a=a_c} = 0$. Using (1.37), if $a < a_c(\phi)$, then $D^* = 0$ and if $a > a_c(\phi)$, then $D^* = W$.

(b) (Fine rate, θ) h is a continuous function of θ on the compact set $[0, \bar{\theta}]$. We have $\frac{\partial h}{\partial \theta} = -a\lambda\gamma t(\theta t + c)^{\gamma-1} < 0$. For $\theta = \theta_c(\phi) = \frac{1}{t}\left[(t-c)\left(\frac{(1-a)}{a\lambda}\right)^{1/\gamma} - c\right]$ we have $h\mid_{\theta=\theta_c} = 0$. It follows that if $\theta < \theta_c(\phi)$, $h > 0$, so from (1.37) $D^* = 0$; and for $\theta > \theta_c(\phi)$, $h < 0$, so from (1.37) $D^* = W$.

(c) (Tax rate, t): h is a continuous function of t on the compact set $[0,1]$. We have that

$$\frac{\partial h}{\partial t} = \gamma(t-c)^{\gamma-1} - a\gamma\left[(t-c)^{\gamma-1} - \lambda\theta(\theta t + c)^{\gamma-1}\right]. \tag{1.38}$$

Since $a \in [0,1]$ the first term on the RHS of (1.38) is greater than the second term. Hence, $\frac{\partial h}{\partial t} > 0$. For $t = t_c(\phi)$, where $t_c(\phi) = c\left(\frac{(1-a)^{1/\gamma} + (a\lambda)^{1/\gamma}}{(1-a)^{1/\gamma} - \theta(a\lambda)^{1/\gamma}}\right) > 0$, we have that $h\mid_{t=t_c} = 0$. It follows that for $t < t_c(\phi)$, $h < 0$, so from (1.37) $D^* = W$ and for $t > t_c(\phi)$, $h > 0$, so from (1.37) $D^* = 0$.

(d) (Loss aversion) h is a continuous function of λ on the compact set $[0, \bar{\lambda}]$, where $\bar{\lambda}$ is the upper limit on the parameter of loss aversion. We have $\frac{\partial h}{\partial \lambda} = -a(\theta t + c)^\gamma < 0$. There exists a critical value $\lambda = \lambda_c(\phi) = \frac{(1-a)}{a\left(\frac{\theta t + c}{t-c}\right)^\gamma}$ for which $h\mid_{\lambda=\lambda_c} = 0$. Hence, using (1.37), if $\lambda < \lambda_c(\phi)$, then $h > 0$, so $D^* = 0$; and if $\lambda > \lambda_c(\phi)$, then $h < 0$, so $D^* = W$. ■

The intuition behind the results in Proposition 6 is identical to that for Proposition 4, which has been already discussed above.

1.6 Data on corner Solutions

A corner solution arises when a subject chooses either to declare nothing ($D = 0$) or their full income ($D = W$). Table 1 shows the incidence of corner solutions (by absolute numbers and percentages) for each treatment. On average, across all 7 questions, 72% of choices in prime & labor treatment and 71% of choices in prime & non-labor treatment were corner solutions. Similarly, 74% of choices in unprimed & labor treatment and 69% of choices in unprimed & non-labor treatment were corner solutions. Across all questions and treatments, 65.1% of the subjects declared their full income and 6.4% declared no income, for a total of 71.5% corner solutions.

1.7 Detailed calculations for the claims in the "other results" subsection 8.2 in the paper

We now give results on the net effects of loss aversion ($d_\lambda = 1$ versus $d_\lambda = 0$), fixing the source of income (either $d_T = 1$ or $d_T = 0$), and restricting attention to risk averse subjects ($d_R = 1$). First, we report the results for labor income ($d_T = 1$).

$$E(Z \mid d_T = 1, d_\lambda = 1, d_R = 1) - E(Z \mid d_T = 1, d_\lambda = 0, d_R = 1) = 0.029. \tag{1.39}$$

Table 1: Number of corner solutions across treatments

Treatments		Q1 ($t = 5\%$)	Q2 ($t = 30\%$)	Q3 ($t = 60\%$)	Q4 ($f = 0$)	Q5 ($f = 1$)	Q6 ($f = 3$)	Q7 *
Primed & labor	D=w	81 (67%)	33 (27%)	29 (24%)	31 (26%)	31 (26%)	67 (56%)	57 (47%)
	D=0	6 (5%)	8 (7%)	10 (8%)	50 (42%)	27 (22%)	3 (2%)	5 (4%)
Primed & Non-labor	D=w	77 (64%)	33 (27%)	30 (25%)	27 (22%)	29 (24%)	60 (50%)	60 (50%)
	D=0	9 (7%)	8 (7%)	14 (12%)	60 (50%)	28 (23%)	7 (6%)	8 (7%)
Unprimed & labor	D=w	82 (65%)	25 (20%)	24 (19%)	31 (25%)	28 (22%)	63 (50%)	58 (46%)
	D=0	11 (9%)	15 (12%)	18 (14%)	60 (48%)	37 (29%)	8 (6%)	10 (8%)
Unprimed & Non-labor	D=w	71 (64%)	37 (34%)	25 (23%)	32 (29%)	28 (25%)	54 (49%)	45 (41%)
	D=0	5 (4%)	7 (6%)	10 (9%)	47 (43%)	31 (28%)	5 (5%)	5 (5%)

* For Q7 the probability of audit is decreasing in declared income with $t = 30\%$ and $f = 2$. For Q1:Q6 the audit probability is fixed at 3%. For Q1:Q3, the fine rate is fixed at $f = 2$ and for Q4:Q6 the tax rate is fixed at $t = 30\%$. Percentage of subjects whom choose corner solutions are in parentheses.

Thus, for labor income, and restricting attention to risk averse subjects, loss averse taxpayers declare 2.9 percentage point more of their income relative to loss seeking subjects. Next, we undertake the same comparison for non-labor income ($d_T = 0$).

$$E(Z \mid d_T = 0, d_\lambda = 1, d_R = 1) - E(Z \mid d_T = 0, d_\lambda = 0, d_R = 1) = -0.012. \tag{1.40}$$

In this case, loss averse taxpayers declare 1.2 percentage point less of their incomes relative to loss seeking subjects, which is a relatively small effect. This effect, even it is very small, cannot be explained by our theoretical predictions, but it indicates mental accounting. If its robustness can be confirmed with additional studies, then it might require an even richer model of entitlements, that we could not have foreseen in our theoretical model.

Now we undertake the same comparisons as we did in (1.39) and (1.40), but we now restrict attention to risk loving subjects ($d_R = 0$). We first give the comparison for labor income.

$$E(Z \mid d_T = 1, d_\lambda = 1, d_R = 0) - E(Z \mid d_T = 1, d_\lambda = 0, d_R = 0) = -0.062. \tag{1.41}$$

Thus, loss averse subjects who are also risk loving, declare 6.2 percentage point less of their labor income, relative to subjects who are loss seeking. Comparing (1.39) and (1.41), risk seeking reverses the cautionary effects of loss aversion and subjects declare 9.1 percentage point less labor income when they are risk loving ($2.9 - (-6.2)$). We now give the analogous comparison for non-labor income.

$$E(Z \mid d_T = 0, d_\lambda = 1, d_R = 0) - E(Z \mid d_T = 0, d_\lambda = 0, d_R = 0) = 0.180. \tag{1.42}$$

Thus, loss averse subjects who are risk loving, declare 18.0 percentage point more of their non-labor income, as compared to loss seeking subjects. Thus, for non-labor income, risk loving behavior is not able to reverse the cautionary effect of loss aversion.

1.8 References cited in footnote 39

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1.9 Demonstrating the robustness of our results

In this section, we successfully demonstrate the robustness of our results to the following extensions. (1) Measurement of the loss aversion parameters on a continuous scale. (2) Adding income levels as independent regressors. (3) Measurement of the loss aversion with different parameters for the probability weighting function. (4) Dropping Marital status from the set of regressors because there are relatively few subjects who are married. (5) Using different model specifications.

Table 2 shows these robustness checks for items (1),(2), and (4). From Table 2, our results are qualitatively the same. None of the coefficients sign or significance changes when we remove marital or add income dummies. Moreover, our results are robust to using a continuous measure of loss aversion. The only change in significance is the coefficients of interaction between risk aversion and labour (treatment dummy) that becomes significant with a continuous measure of loss aversion.

Table 3 examines the robustness of our results to assumptions about probability weighting. Recall that we estimate loss aversion by $\lambda = \left(\frac{w(1-p)}{w(p)}\right)\left(\frac{x}{z}\right)^{\gamma}$. For the case $p = 0.5$, we assumed

$\frac{w(1-p)}{w(p)} = 1$. Hence, we estimated loss aversion by $\lambda = \left(\frac{x}{z}\right)^{\gamma}$. Our estimation of γ also relies on assuming $w(0.5) = 0.5$. We relax these assumptions by examining the robustness of our results to different values of probability weights from the literature. In particular, we use the Abdellaoui (2000) and Fehr-Duda et al. (2010) estimates of probability weighting functions to estimate a continuous measure of loss aversion. Gächter et al. (2022) consider the Abdellaoui (2000) estimates as an upper bound for the importance of differential probability weightings of gains and losses where $\frac{w(1-p)}{w(p)} = 0.86$. However, the Fehr-Duda et al. (2010) estimates indicate $\frac{w(1-p)}{w(p)} = 1.16$. Our results are robust to these changes as the sign and significance of coefficients remain the same.

Table 4 explores other model specifications. We opted for Tobit regression because of the high number of corner choices by our subjects. However, we could also have used OLS or considered different levels of evasion in an ordered probit model. We show that our results are robust to using ordered probit or OLS regressions with different dependent variables.

Table 2: Tobit regression robustness checks

	Dependent variable:		
	Proportion of declared income		
	(1)	(2)	(3)
Tax	−1.030***	−1.029***	−1.030***
	(0.082)	(0.082)	(0.082)
Fine	0.290***	0.291***	0.290***
	(0.016)	(0.016)	(0.016)
Probability of detection	0.067*	0.068**	0.066*
	(0.034)	(0.034)	(0.034)
Loss aversion	0.177***	0.043**	0.181***
	(0.059)	(0.019)	(0.059)
Risk aversion	−0.017	0.041	−0.016
	(0.050)	(0.071)	(0.051)
Labor	0.040	0.066	0.048
	(0.051)	(0.054)	(0.051)
Prime	0.052**	0.041*	0.052**
	(0.025)	(0.025)	(0.025)
Time	−0.005***	−0.005***	−0.005***
	(0.001)	(0.001)	(0.001)
age	0.048***	0.048***	0.048***
	(0.006)	(0.006)	(0.006)
Gender	0.211***	0.198***	0.209***
	(0.026)	(0.026)	(0.026)
Education	−0.118***	−0.114***	−0.120***
	(0.032)	(0.032)	(0.032)
Religion	0.094***	0.095***	0.097***
	(0.028)	(0.028)	(0.028)
Loss aversion:Risk aversion	−0.199***	−0.090*	−0.200***
	(0.075)	(0.047)	(0.075)
Loss aversion:Labor	−0.236***	−0.065***	−0.240***
	(0.082)	(0.024)	(0.082)
Risk aversion:Labor	−0.017	−0.220**	−0.021
	(0.071)	(0.095)	(0.071)
Loss aversion:Risk aversion:Labor	0.292***	0.219***	0.296***
	(0.105)	(0.060)	(0.105)
Income1			−0.091*
			(0.055)
Income2			−0.037
			(0.046)
Income3			−0.033
			(0.044)
Income4			−0.042
			(0.043)
logSigma	−0.427***	−0.430***	−0.427***
	(0.021)	(0.021)	(0.021)
Constant	−0.458***	−0.454***	−0.421***
	(0.134)	(0.137)	(0.140)
N	3339	3339	3339

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are in parentheses. As compared to our main model of interest, model (1) drops Marital, model (2) uses a continuous measure of loss aversion, model (3) includes income dummies.

Table 3: Tobit regression with continuous loss aversion under various assumptions of probability weights

	Dependent variable:		
	Proportion of declared income		
	(1)	(2)	(3)
Tax	-1.029^{***}	-1.032^{***}	-1.029^{***}
	(0.082)	(0.083)	(0.082)
Fine	0.291^{***}	0.294^{***}	0.291^{***}
	(0.016)	(0.016)	(0.016)
Probability of detection	0.068^{**}	0.071^{**}	0.068^{**}
	(0.034)	(0.035)	(0.034)
Loss aversion	0.043^{**}	0.053^{***}	0.049^{**}
	(0.019)	(0.014)	(0.021)
Risk aversion	0.041	0.038	0.062
	(0.071)	(0.059)	(0.080)
Labor	0.066	0.063	0.075
	(0.054)	(0.052)	(0.059)
Prime	0.041^{*}	0.043^{*}	0.041
	(0.025)	(0.025)	(0.025)
Time	-0.005^{***}	-0.005^{***}	-0.005^{***}
	(0.001)	(0.001)	(0.001)
Age	0.048^{***}	0.047^{***}	0.048^{***}
	(0.006)	(0.006)	(0.006)
Gender	0.198^{***}	0.197^{***}	0.198^{***}
	(0.026)	(0.026)	(0.026)
Education	-0.114^{***}	-0.118^{***}	-0.114^{***}
	(0.032)	(0.032)	(0.032)
Religion	0.095^{***}	0.096^{***}	0.097^{***}
	(0.028)	(0.028)	(0.028)
Loss aversion:Risk aversion	-0.090^{*}	-0.086^{**}	-0.099^{*}
	(0.047)	(0.035)	(0.051)
Loss aversion:Labor	-0.065^{***}	-0.059^{***}	-0.070^{**}
	(0.024)	(0.021)	(0.027)
Risk aversion:Labor	-0.220^{**}	-0.161^{**}	-0.265^{**}
	(0.095)	(0.080)	(0.108)
Loss aversion:Risk aversion:Labor	0.219^{***}	0.172^{***}	0.235^{***}
	(0.060)	(0.046)	(0.065)
logSigma	-0.430^{***}	-0.428^{***}	-0.430^{***}
	(0.021)	(0.022)	(0.021)
Constant	-0.454^{***}	-0.455^{***}	-0.465^{***}
	(0.137)	(0.135)	(0.138)
N	3339	3339	3339

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are in parentheses. Model (1) assumes $w^{-}(0.5) = w^{+}(0.5) = 0.5$. Model (2) uses parameters from Abdellaoui (2000) to calculate $\frac{w^{+}(0.5)}{w^{-}(0.5)}$ and $w^{+}(0.5)$. Model (3) uses parameters from Fehr-Duda et al. (2010) to calculate $\frac{w^{+}(0.5)}{w^{-}(0.5)}$ and $w^{+}(0.5)$.

Table 4: Ordered probit and ordinary least square specifications

	(1)	(2)
Tax	1.616***	−44.559***
	(0.129)	(3.764)
Fine	−0.449***	12.756***
	(0.026)	(0.704)
Probability of detection	−0.101*	1.090
	(0.053)	(1.436)
Loss aversion	−0.294***	6.432**
	(0.091)	(2.740)
Risk aversion	0.023	−1.599
	(0.079)	(2.305)
Labor	−0.071	2.639
	(0.081)	(2.345)
Prime	−0.071*	3.251***
	(0.039)	(1.136)
Income1	0.151*	13.825***
	(0.085)	(1.265)
Income2	0.017	30.187***
	(0.071)	(1.263)
Income3	0.087	45.922***
	(0.069)	(1.366)
Income4	0.059	61.783***
	(0.068)	(1.567)
Time	0.007***	−0.226***
	(0.002)	(0.052)
Age	−0.073***	1.612***
	(0.009)	(0.236)
Gender	−0.320***	8.379***
	(0.040)	(1.155)
Education	0.182***	−4.705***
	(0.049)	(1.379)
Religion	−0.157***	3.757***
	(0.043)	(1.301)
Loss aversion:Labor	0.352***	−12.430***
	(0.128)	(3.853)
Loss aversion:Risk aversion	0.306***	−6.452*
	(0.116)	(3.449)
Risk aversion:Labor	0.032	−1.160
	(0.111)	(3.243)
Loss aversion:Risk aversion:Labor	−0.424***	13.328***
	(0.162)	(4.818)
0|1	−2.164***	
	(0.218)	
1|2	−1.544***	
	(0.217)	
2|3	−0.629***	
	(0.217)	
Constant		−25.623***
		(5.656)
N	3339	3339

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are in parentheses. Model (1) shows ordered probit regression results when the dependent variable is evasion (Z). For this we constructed four categories of our dependent variable ($Z = 0; 0 < Z < \frac{1}{2}W; \frac{1}{2}W \leq Z < W; Z = W$) where W is subject's income in the experiment. Model (2) reports ordinary least square results when the dependent variable is declared income.

1.10 Marginal effects of Tobit model

Table 5: Marginal Effects of Tobit model

	AME on Z	ME at Means	AME on $E(Z^*\|0<Z^*<1)$	AME on $P(0<Z^*<1)$
Tax	-1.030***	-1.030***	-0.494***	0.247***
	(0.0819)	(0.0819)	(0.0379)	(0.0257)
Fine	0.290***	0.290***	0.139***	-0.0694***
	(0.0161)	(0.0161)	(0.0070)	(0.0051)
Probability of detection	0.0666*	0.0666*	0.0317**	-0.0174*
	(0.0341)	(0.0341)	(0.0161)	(0.0096)
Loss aversion	0.0244	0.0251	0.0112	-0.0060
	(0.0254)	(0.0254)	(0.0121)	(0.0060)
Risk aversion	-0.0478*	-0.0521**	-0.0219*	0.0128*
	(0.0264)	(0.0264)	(0.0125)	(0.0066)
Labor	0.0179	-0.0004	0.0092	0.0000
	(0.0249)	(0.0253)	(0.0119)	(0.0060)
Prime	0.0522**	0.0522**	0.0250**	-0.0125**
	(0.0251)	(0.0251)	(0.0120)	(0.0060)
Time	-0.0048***	-0.0048***	-0.0023***	0.0012***
	(0.0012)	(0.0012)	(0.0005)	(0.0003)
Age	0.0480***	0.0480***	0.0230***	-0.0115***
	(0.0060)	(0.0060)	(0.0028)	(0.0016)
Gender	0.211***	0.211***	0.101***	-0.0506***
	(0.0255)	(0.0255)	(0.0121)	(0.0065)
Education	-0.118***	-0.118***	-0.0563***	0.0276***
	(0.0316)	(0.0316)	(0.0150)	(0.0074)
Religion	0.0936***	0.0936***	0.0453***	-0.0207***
	(0.0275)	(0.0275)	(0.0134)	(0.00567)
N	3339	3339	3339	3339

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors are in parentheses.

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