Dissertation

Taxpayers' Misperceptions and Two Novel Behavioral Interventions to Counter Tax Evasion

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This document was submitted as a dissertation in December 2019 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of of Andrew Parker (chair), Rafaele Vardavas and Sebastian Linnemayr. The external reader was Kim Bloomquist.

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Abstract

The US Government loses approximately $381 billion in unpaid taxes annually (IRS, 2019a). If collected, these unpaid taxes would have increased total federal revenues by about 11.5% in 2018, an amount that would have covered almost half of the federal budget deficit that year. The government (and in this case, the IRS) has mostly used conventional tools like tax audits and penalties to address this problem. However, tax audits are costly. Even with very low overall audit rates of less than 1%, IRS enforcement costs are around $4.7 billion per fiscal year (IRS, 2018, 2019b). Moreover, tax audits are not always successful in detecting tax evasion, and hence remain a limited solution. Thus, there is a need for less expensive but effective ways to increase taxpayer compliance.

Exploring such intervention opportunities for tax evasion is the main goal of this dissertation. The dissertation focuses on the behavioral aspects of tax evasion, specifically, on perceptions about tax evasion and key elements of the U.S. federal tax system. It shows that the US taxpayers have considerable misperceptions about their effective federal income tax rates and the penalties for underreporting taxes. It also provides evidence suggesting that these misperceptions can exacerbate tax evasion. Therefore, reducing or eliminating these misperceptions may prompt people to be more tax compliant. For that purpose, two behavioral interventions are proposed. The goal of the proposed interventions is to reduce tax evasion by countering misperceptions about effective tax and penalty rates. The proposed interventions are simple, relatively minor additions to federal income tax Form 1040. They could substantially reduce tax evasion rates by correcting taxpayers' misperceptions about their tax burden and the penalties for underreporting taxes. If successful, this reduction in tax evasion could potentially help the IRS to collect billions in additional tax revenues annually. The intervention designed was informed by principles from a prominent intervention framework called EAST (The Behavioural Insights Team, 2014). The ALP Tax Evasion Survey and publicly accessible IRS data were used to preliminarily assess the impact of the interventions on tax evasion.

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Introduction

The US Government loses approximately $381 billion in unpaid taxes annually (IRS, 2019a). If collected, these unpaid taxes would have increased total federal revenues by about 11.5% in 2018, an amount that would have covered almost half of the federal budget deficit that year. The government (and in this case, the IRS) has mostly used conventional tools like tax audits and penalties to address this problem. However, tax audits are costly. Even with very low overall audit rates of less than 1%, IRS enforcement costs are around $4.7 billion per fiscal year (IRS, 2018, 2019b). Moreover, tax audits are not always successful in detecting tax evasion, and hence remain a limited solution. Thus, there is a need for less expensive but effective ways to increase taxpayer compliance.

Recent developments within behavioral science provide potentially effective leads for reducing tax evasion, often at quite low cost. In one example outside the tax domain, federal vendors are required to pay an ***industrial funding fee***, which is calculated based on self-reported quarterly sales. Federal vendors report their sales to the General Services Administration (GSA) using an online form. In 2014, the GSA simply moved the signature box from the bottom to the top of the online form for some of the vendors. This was done to make ethics salient before self-reporting and, hence, encourage vendors to be more honest in reporting their sales. This idea was experimentally tested by behavioral scientists Shu, Mazar, Gino, Ariely and Bazerman in 2012. It worked. The cost to the GSA to move the signature box to the top was nearly nothing , but the change produced an extra $1.59 million in fees collected from these vendors within only three months (Office of Evaluation Sciences, 2015).

Exploring similar intervention opportunities for tax evasion is the main goal of this dissertation. For that purpose, the dissertation focuses on the behavioral aspects of tax evasion, specifically, on perceptions about tax evasion and key elements of the U.S. federal tax system. It addresses the following research questions:

1) How well do individual perceptions of audit rates, penalty rates and effective tax rates correspond to the actual audit, penalty and tax rates? To what extent are these perceptions biased? What individual characteristics appear to be driving these biases?
2) How do perceptions of audit rates, penalty rates and effective tax rates relate to tax evasion? Specifically, what are the tax evasion elasticities with respect to perceived audit rates, perceived penalties and perceived effective tax rates?
3) Using the answers to the questions above, in conjunction with a behavioral economic framework (namely, the EAST framework developed by UK's Behavioral Insights Team), what policy opportunities or policy elements are more likely to improve tax compliance?

Before answering these questions, the standard economic model for tax evasion is reviewed in Chapter 1. The first and the second sets of questions are examined in Chapter 2 and Chapter 3, respectively. The findings of these two chapters provide the basis for two behavioral interventions proposed in Chapter 4.

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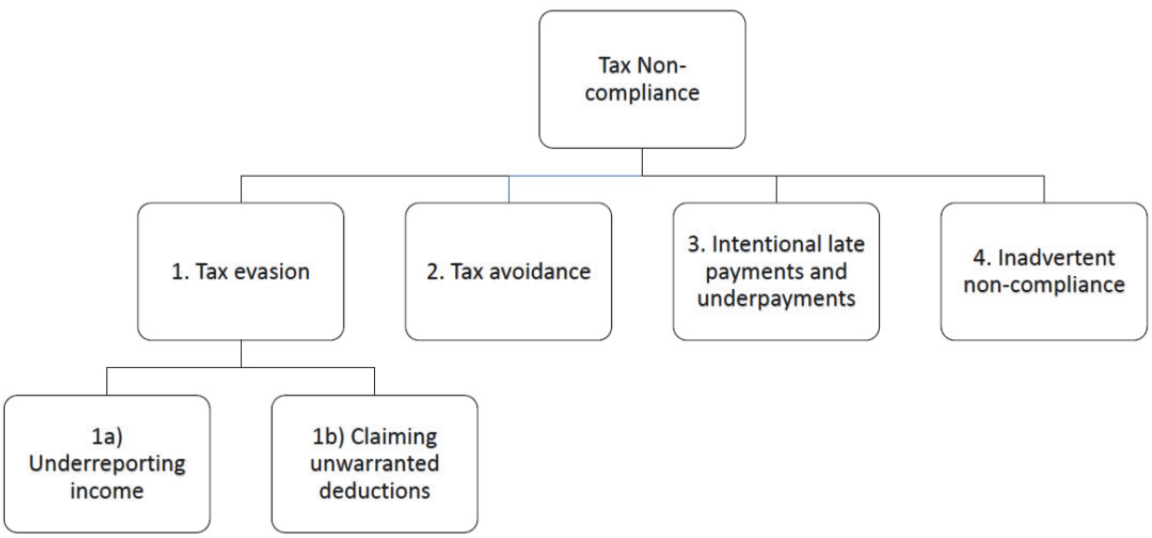
Chapter 1: Review of the Existing Literature Relevant to Tax Evasion

Introduction

Erich Kirchler, in his *The Economic Psychology of Tax Behavior*, defines “tax non-compliance” as “failures to meet tax obligations whether or not those failures are intentional,” which furthermore “does not necessarily imply the violation of law.”(Kirchler, 2007, p. 21). Indeed, this “most inclusive” definition encompasses all major types of tax non-compliance as illustrated in **Figure 1.1**. I briefly discuss each category, which represent different problems in terms of their nature, legality and taxpayers’ intentions.

Figure 1.1: Major Types of Tax Non-compliance



The first type of noncompliance in this figure is tax evasion. *Tax evasion* can be defined as an illegal understatement of one’s taxes by fully or partially underreporting income (including income from unlawful sources) and/or claiming unwarranted tax deductions. If such understatement is undetected by tax authorities, then the tax evader will end up underpaying taxes. If detected, then the evader may be penalized. While tax evasion involves illegal actions or inactions, tax avoidance is often legal. *Tax avoidance* is reducing one’s tax obligations by exploiting or misusing legal loopholes. Stricter and narrower definitions of non-compliance may not include tax avoidance as a type of non-compliance since it usually does not involve the violation of law. However, James and Alley (2002) argue that tax avoidance is a non-compliant behavior:

> While some commentators see non-compliance only as an evasion problem, this does not seem to capture the full nature of the problem. Clearly tax evasion is a form of non-compliance. However, if taxpayers go to inordinate lengths to reduce their liability this could hardly be considered 'compliance' either. Such activities might include engaging in artificial transactions to avoid tax, searching out every possible legitimate deduction, using delaying tactics and appeals wherever this might reduce the flow of tax payments and so on. 'Tax exiles' even seem to prefer to emigrate rather than fulfill their obligations as citizens. Even if such activities are within the letter of the law, they are clearly not within the spirit of the law. Compliance might therefore be better defined in terms of complying with the spirit as well as the letter of the law. (p.31)

The third category in the figure is *intentional late payments and underpayments of taxes.* Taxpayers can be non-compliant by intentionally delaying their tax payments or underpaying (or failure to pay) their taxes even when their tax obligations are known to tax authorities. The final category is *inadvertent non-compliance.* This category includes under- or overpayments due to calculation errors or lack of knowledge, unintentionally missing tax deadlines etc.

It seems that, out of these types of noncompliance, researchers have been most interested in tax evasion. At the very least, the search phrase "tax evasion" yields almost twice as many results as "tax avoidance" in the databases of academic literature like Google Scholar, JSTOR and ScienceDirect.[1] This interest can be explained partially by the nature of tax evasion. Tax evasion is illegal, and unlike the other major types of tax non-compliance, it has an uncertainty element, i.e., a taxpayer who considers evasion faces uncertainty about his/her actions being detected by the tax authorities. Thus, while legal scholars may find tax evasion interesting because it is illegal, economists and behavioral scientists alike have been frequently viewing it as a case of decision-making under uncertainty (Allingham & Sandmo, 1972; Gahramanov, 2009; Kolm, 1973; Sandmo, 1981, 2005; Srinivasan, 1973; Yitzhaki, 1974).

Decision-making under uncertainty is at the core of the most popular and influential model of tax evasion in the economics literature. This model was developed by Allingham and Sandmo (1972) and is the focus of this chapter. In this chapter, I first briefly describe the model and discuss its key theoretical conclusions, as well as the empirical evidence relating to these conclusions. Then I discuss some key extensions of this model. Finally, I talk about its limitations as a decision-making tool (i.e., the taxpayers' perspective) and as a policy-making instrument (i.e., the policy-makers' perspective). The purpose of this chapter is to identify gaps in the standard economic theory of tax evasion and discuss how behavioral science can help to fill them.

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[1] During a series of searches conducted on August 4th, 2018, Google Scholar generated over 94 thousand results for "tax evasion" and about 54 thousand results for "tax avoidance". In JSTOR, the numbers were 7,054 and 3,510, respectively. In ScienceDirect, the results were 3,247 for "tax evasion" and 1,511 for "tax avoidance".

Basic Neoclassical Model and Its Theoretical Conclusions

The traditional economics framework is the most commonly used model in the tax compliance literature. It assumes that individuals make rational decisions regarding tax compliance based on the cost and benefits given the objective characteristics of the tax system, including audit rates and penalties. Michael Allingham and Agnar Sandmo in their seminal 1972 paper "Income Tax Evasion: A Theoretical Analysis" formally developed a model for an individual's decision to evade taxes. A similar model of tax evasion was independently developed by Srinivasan (1973) at about the same time. These models, to some extent, are based on Becker's (1968) model of expected utility from committing a criminal offense. In both models, a taxpayer takes actions that maximize his/her expected utility function that depends on the probability of detection and the penalty rate. By optimizing in this way, the taxpayer decides if and by how much he/she should evade taxes.

According to Allingham and Sandmo (1972), the basic static form of this expected utility function is as follows:

$$E[U] = (1-p)U(W-\theta X) + pU\big(W-\theta X-\pi(W-X)\big). \qquad (1.1)$$

In this equation, p is the probability that the taxpayer will be audited and the actual income W will be known to the tax authority; X is the declared income; θ is the tax rate and π is the penalty rate. Using this equation, Allingham and Sandmo (1972) derived a number of conclusions about tax underreporting. Since some of these conclusions will be empirically tested in the following chapters, it will be useful to briefly discuss them here.[2]

Theoretical conclusion 1: *A risk-averse taxpayer will underreport her[3] income, if the tax rate is bigger than the expected penalty rate (i.e., the product of the penalty rate and the probability of detection):*

$$p\pi < \theta. \qquad (1.2)$$

Note that this condition assumes that the taxpayer is risk-averse (i.e., if the taxpayer faces two actions with the same expected outcome, she will choose the one with the lower risk). Mathematically, this risk-aversion assumption translates into concavity of the taxpayer's utility function, which means that the second-order derivative of the utility function, $U''(x) < 0$ for all values of x. The concavity of the function, in its turn, allows one to derive inequality (1.2).

[2] The authors derived some of these conclusions using the Arrow-Pratt measures of risk aversion: absolute risk aversion and relative risk aversion, which are mathematically expressed as $R_A = -\frac{U''(x)}{U'(x)}$ and $R_R = -\frac{U''(x)\cdot x}{U'(x)}$, respectively. In this context, x is income. Thus, absolute risk aversion measures the rate at which marginal utility decreases when income x is increased by one unit (say by \$1). Relative risk aversion measures the rate at which marginal utility decreases when income is increased by one percent. One can also think of it as the income-elasticity of marginal utility.

[3] While obviously a taxpayer can be male or female, from now on throughout this chapter I will use pronouns "she", "her" instead of "he/she" and "his/her".

Sandmo (2012) points out that although this condition does not refer to the taxpayer's degree of risk aversion, the extent of the underreporting depends on it:

> "It is worth noting that this condition makes no reference to the taxpayer's degree of risk aversion or more generally to his preferences. The *extent* of his underreporting, on the other hand, will obviously depend on the shape of his utility function and his degree of risk aversion."

While this theoretical conclusion is intuitive and perfectly reasonable (or rather perfectly rational since it means that a taxpayer will cheat when the expected loss from evading is lower than the loss from paying taxes), some researchers have found that this conclusion is not supported by available empirical data. Under existing audit, penalty, and tax rates, most taxpayers should evade, yet the actual tax compliance rates are higher than predicted (Alm, McClelland, & Schulze, 1992; Alm, McKee, & Beck, 1990; Frey & Feld, 2002; Pommerehne & Frey, 1992). For example, Alm, McClelland, et al. (1992) noted that with an audit rate of less than 1 percent and a penalty rate of only 75 percent of unpaid taxes, taxpayers would have to exhibit unusually high risk aversion levels in order to generate the actual compliance rates in the US. Similarly, other researchers (Frey & Feld, 2002; Pommerehne & Frey, 1992) demonstrated that unrealistically high risk aversion levels have to be assumed to obtain actual compliance rates under the prevailing audit, penalty and tax rates in Switzerland.

These researchers based their criticism on the actual values of audit, penalty and tax rates. However, Sandmo (2012) argues that "what matters for taxpayer's decision is not the objective frequency of audit but his subjective perception of what the probability of discovery is." This claim (which implies a departure from the assumption of perfect knowledge) can be extended to include tax and penalty rates, and the inequality (1.2) can be written in terms of subjective perceptions only. There are not that many, if any, studies that tested this subjective perception condition. The American Life Panel's Tax Evasion survey data provides a unique opportunity to conduct this test. These data will be used to examine, among other things, this theoretical conclusion with subjective audit, penalty and tax rates in Chapter 3.

Theoretical conclusion 2: *The amount of declared income (X) that maximizes the taxpayer's expected utility is positively related to actual income (W) if the penalty rate $\pi \geq 1$ (i.e., 100%), assuming decreasing absolute risk aversion*[4]. Mathematically this conclusion can be expressed as:

$$\frac{\partial X}{\partial W} > 0 \text{ if } \pi \geq 1. \qquad (1.3)$$

There are three other interesting conditions that will make the derivative $\partial(X/W)$ unambiguously positive. Yet, these conditions were not explicitly considered by Allingham and

[4] Mathematically, decreasing absolute risk aversion means that as income increases the absolute risk aversion measure, R_A, which is defined in the previous footnote, will decrease. In the context of this model, this assumption implies that as taxpayer's actual income increases, she will underreport more dollars.

Sandmo in their 1972 paper. First, one can show that *when* $(\theta - \pi) > 0$ *or* $\theta > \pi$, *(i.e., when tax rate is bigger than the penalty rate) and* $\pi < 1$, *then a risk-averse taxpayer will declare more income as the actual income increases*:

$$\frac{\partial X}{\partial W} = \frac{\theta(1-p)U''(Y)+(\theta-\pi)(1-\pi)pU''(Z)}{\theta^2(1-p)U''(Y)+(\theta-\pi)^2pU''(Z)} > 0 \; if \; \theta > \pi \; and \; \pi < 1 \qquad (1.4)$$

where $Y = W - \theta X$ and $Z = W - \theta X - \pi(W - X)$.

The second case is *when* $(\theta - \pi) < 0$ *or* $\theta < \pi$, *(i.e., when tax rate is smaller than the penalty rate) and* $\pi > 1$. And the third case is *when* $\theta = \pi$ *or* $\pi = 1$. Thus, based on the Allingham and Sandmo (A-S) model, one can hypothesize that when $\theta > \pi$ and $\pi < 1$, or when $\pi > 1$ and $\pi > \theta$, or when either $\theta = \pi$ or $\pi = 1$, then increasing income will increase declared income.

These cases are plausible: for instance, the accuracy-related[5] penalty rate for underreporting individual income tax is currently 20% in the US (IRS, 2017b), whereas the effective tax rate for high-income ($500,000 and above) taxpayers is substantially higher than 20% (own calculations based on data in Table 1.1 in (IRS, 2017a)). It is also not hard to imagine a scenario when the penalty rate is equal to the tax rate, or a scenario when the penalty rate is more than 100% and greater than the tax rate. Thus, it is important to consider these cases too. Moreover, note that in all three cases, the assumption of decreasing absolute risk aversion can be relaxed.

Different assumptions and conditions determine the effect of actual income on declared income in the A-S model. Theoretically, this makes the direction of the effect ambiguous. Similar ambiguity is observed in empirical studies. For example, some studies based on field data found evidence suggesting a negative correlation between actual income and declared income (Clotfelter, 1983; Pommerehne & Weck-Hannemann, 1996). Nonetheless, one of these studies (Clotfelter, 1983) also detected a positive association between wages, which were subject to third party reporting, and declared income: the larger was the share of wages in the total income, the higher was the reported income. Contrary to the results of these field studies, some experimental studies (Alm, Jackson, & McKee, 1992; Alm et al., 1990) found positive relationship between actual and declared income. A similarly positive but statistically insignificant relationship was found by Alm, Jackson, and McKee (1993) in another lab-experiment study. A statistically insignificant relationship between adjusted gross income and underreported taxable income was also observed in an econometric analysis of pooled 1982 and 1985 US Tax Compliance Measurement Program (TCMP) data (Feinstein, 1991). However, when TCMP data for 1982 and 1985 were analyzed separately, Feinstein (1991) found a statistically significant quadratic relationship between income and underreporting. This finding suggests that actual income may be related to reported income in a non-linear way.

[5] An accuracy-related penalty maybe applied to a taxpayer if taxes are underpaid because: 1) taxpayer shows negligence or disregard of rules or regulations; 2) taxpayer substantially understates the income tax; 3) taxpayer claims tax benefits for a transaction that lacks economic substance, or; 4) taxpayer fails to disclose a foreign financial asset (IRS, 2017b).

Theoretical conclusion 3: *As the actual income increases, the proportion of income declared increases, stays the same or decreases if relative risk aversion is an increasing, constant or decreasing function of income[6], respectively.*

The authors reached this conclusion by analyzing the sign of the derivative $\partial(X/W)/\partial W$, which can be expressed as:

$$\frac{\partial(X/W)}{\partial W} = \frac{1}{W^2}\frac{\theta(1-p)U''(Y)Y+(\theta-\pi)pU''(Z)Z}{D} \qquad (1.5)$$

where $Y = W - \theta X$; $Z = W - \theta X - \pi(W - X)$ and $D = \theta^2(1-p)U''(Y) + (\theta - \pi)^2 pU''(Z)$. However, again they did not discuss in their paper the case when $(\theta - \pi) \geq 0$ or $\theta \geq \pi$, i.e., when the tax rate is at least as big as the penalty rate. In this case, the sign of the derivative $\partial(X/W)/\partial W$ is also unambiguously positive. This means that *when the tax rate is bigger than or equal to the penalty rate, an increase in actual income will lead to a higher fraction of the income declared to the tax authorities, if a person is risk-averse.* In other words, an increase in actual income may improve compliance when the tax rate is at least as big as the penalty rate.

A proposition related to this theoretical conclusion was also made by Srinivasan (1973). Srinivasan (1973) states that given a progressive tax function, and a probability of detection independent of income[7], the wealthier the person, the larger is the optimal proportion by which the taxpayer will understate the income (i.e., $\partial(X/W)/\partial W < 0$).

This proposition, at least the direction of the relationship between wealth/income and compliance, has some supporting empirical evidence. Through a lab experiment, Alm, Deskins, and McKee (2009) detected a statistically significant negative relationship between income and percentage of income reported. In another lab experiment, Alm, Bloomquist, and McKee (2017) found that wealth is negatively associated with both filing rate and reporting rate (taxes paid as a percentage of taxes owed). A negative association between income and percentage of income reported was also found by Park and Hyun (2003), although that correlation was not statistically significant. Frey and Feld (2002) obtained similar results by analyzing field data from Swiss cantons. Considering this empirical evidence, one may conclude that taxpayers' utility function in the A-S model should have qualities of either decreasing or constant relative risk aversion.

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[6] Increasing, constant and decreasing relative risk aversion assumptions mathematically can be expressed as $R_R'(x) > 0$, $R_R'(x) = 0$, and $R_R'(x) < 0$, respectively. Here R_R is a relative risk aversion measure, and x is income. Economic interpretation of these assumptions is analogous to the ones in the portfolio and insurance analysis. Under increasing (decreasing) relative risk aversion, as individual's wealth/income increases, she holds a smaller (larger) percentage of wealth in risky assets. In a taxpayer's case, the risky asset is the undeclared income.

[7] While the US individual income tax system is progressive, probability of detection is likely not independent of income. High-income individuals are significantly more likely to be audited than low- and middle-income taxpayers in the US.

Theoretical conclusion 4: *The direction of the relationship between the tax rate and reported income can be either negative or positive. It will be negative when absolute risk aversion is constant or increasing. It can be positive, negative or zero when absolute risk aversion is decreasing.*

By conducting a comparative static analysis, the authors explain this ambiguity with two opposing forces: income effect and substitution effect. Yitzhaki (1974) mathematically proved that under certain conditions, the A-S model will have no substitution effect and will yield positive relationship between tax rate and reported income. These conditions are when "the fine is imposed on the evaded tax" (which is the case in countries like the US, Israel and Switzerland) and "the taxpayer has an absolute risk aversion which decreases with income" (Yitzhaki, 1974).

Yitzkhaki's theoretical prediction contradicts findings of numerous empirical studies.[8] For instance, there are several studies suggesting that marginal tax rates are negatively associated with the share of income reported to tax authorities in Switzerland (Frey & Feld, 2002; Pommerehne & Frey, 1992; Pommerehne & Weck-Hannemann, 1996). A similar relationship was observed by Clotfelter (1983) in his analysis of the US TCMP data for 1969. TCMP data for 1982 and 1985, when analyzed separately[9], also yielded negative correlation between underreported income and marginal tax rates (Feinstein, 1991). There are also lab-experiment studies that challenge Yitzkhaki's conclusion, such as Alm, Jackson, et al. (1992), Park and Hyun (2003) and Alm, Deskins, et al. (2009). These studies found a statistically significant *negative* correlation between tax rate and declared income or proportion of income reported. Interestingly, although these three studies conducted separate lab experiments at different times and different places, their regression models for reported income generated comparable coefficients for tax rates.

These empirical studies imply that holding everything else constant, when tax rates are increased, taxpayers may become less compliant. One may also expect that decreasing tax rates may lead taxpayers to be more compliant. Nevertheless, this response may not be as strong as taxpayers' response to a tax increase. To put it differently, in terms of compliance, taxpayers may be more responsive to a tax rate increase than to a decrease of the same magnitude. This hypothesis is consistent with the prospect theory and the concept of loss aversion (Kahneman & Tversky, 1979, 1984). According to the concept of loss aversion, taxpayers will lose more utility from a tax hike than they will gain from an equal amount tax cut. This asymmetric change can potentially generate an asymmetric response by taxpayers to tax rate increases and decreases.

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[8] This contradiction is sometimes called *the Yitzhaki puzzle*.

[9] Surprisingly, when the TCMP data for these two years were combined and examined, the sign of the correlation between these two variables changed (Feinstein, 1991). Thus, pooled TCMP data for 1982 and 1985 provided evidence actually supporting Yitzkhaki's prediction.

If this asymmetric response to tax rate changes exists, then it may have an important policy implication. To be specific, if a government decides to increase the tax rate, then tax compliance may go down. But if later the tax rate is set back to its original value, tax compliance may not be restored to its pre-change level. Because of this potential policy implication, it would be useful to empirically test this hypothesis of an asymmetric response to changes in the tax rate. This hypothesis will be tested with the American Life Panel's Tax Evasion survey data in the next chapters.

Theoretical conclusion 5: *Increasing the penalty rate will increase compliance (i.e., will increase the proportion of the actual income reported).*

This theoretical conclusion has also been mathematically derived through comparative static analysis of the basic A-S model. Nevertheless, it is more intuitive than the ones described above since one would expect, even without a mathematical model, that higher penalties are likely to discourage evasion behavior.

While empirical evidence generally supports this conclusion, some studies failed to detect a statistically significant relationship between tax compliance and the penalty rate. Examples are studies by Pommerehne and Frey (1992) and by Pommerehne and Weck-Hannemann (1996). These researchers ran regression analyses with the field data for Swiss cantons for various years. Their regression models had the proportion of true income concealed from the tax authorities as the dependent variable, and used penalty rates as one of the independent variables. Although the coefficients for penalty rates were negative as the A-S model predicts, they were statistically insignificant. The magnitude of these coefficients were also smaller than those for the probability of detection. Similar results were obtained in lab experiments conducted by Alm, Jackson, et al. (1992), even though they used the amount of declared income as the dependent variable in their regression models. In another more recent lab experiment, Maciejovsky, Kirchler, and Schwarzenberger (2007) also found that the effect of penalties on tax compliance are smaller than those for audits. This suggests that, in terms of reducing evasion, increasing penalty rates may be less effective than increasing audit rates by the same amount.[10] Nevertheless, there are empirical studies that found a statistically significant positive relationship between compliance and the penalty rate (Frey & Feld, 2002; Park & Hyun, 2003). Yet, even in these studies the estimated effect of the penalty rates on compliance was not very large, and usually smaller than the effect of the detection probabilities. The empirical evidence then suggests that the penalty rates are, at best, only moderately effective as a policy instrument in deterring tax evasion.

Theoretical conclusion 6: *Increasing the probability of detection will increase compliance (i.e., will increase the proportion of income reported).*

[10] Still, an important point that should be kept in mind is that audits and penalties are used in tandem, and one without the other is not likely to be a very effective compliance-enforcement tool.

Just like the previous theoretical conclusion, this outcome can be mathematically derived but is also intuitive. To illustrate, let's consider two extreme cases: 1) when it is certain that an evader will be caught, i.e., the probability of detection is one ($p = 1$); and 2) when it is certain that an evasion will not be detected, i.e., the probability of detection is zero ($p = 0$). In the former case, it would be sensible to fully comply since any underreporting will be detected and penalized. Indeed, in this case, the expected utility function in equation (1.1) will be just equal to $U\big(W - \theta X - \pi(W - X)\big)$, and it will be maximized when $X = W$ or when a taxpayer fully reports her income. In the latter case, a sensible action would be underreporting all income, since it will not be detected and penalized anyways. In this case, the A-S model predicts that the expected utility function will be equal to $U(W - \theta X)$, and a utility-maximizing taxpayer should declare no income, i.e., $X = 0$.

Still, there is some experimental evidence suggesting that some taxpayers will comply even when the probability of detection is nearly zero or even zero. Alm, McClelland, et al. (1992) observed a substantial level of compliance among individuals who were assigned to no-audit groups in a lab experiment. Although the probability of audit was zero, the average compliance in these groups was 20 percent with some variation ranging between 5.3 and 35.8 percent.[11] Furthermore, the compliance level for these groups did not decay over 15 rounds of the experiment. Nonetheless, the authors found a statistically significant positive association between audit rates and compliance, and concluded that the "rate of compliance rises in a *non-linear* [italics added] way as the probability of detection increases" (Alm, McClelland, et al., 1992). There are numerous other empirical studies that also found a statistically significant positive correlation between audit rates and compliance levels (Alm et al., 2017; Alm, Deskins, et al., 2009; Alm, Jackson, et al., 1992; Maciejovsky et al., 2007; Park & Hyun, 2003; Pommerehne & Frey, 1992; Pommerehne & Weck-Hannemann, 1996).

As already mentioned above, in terms of enforcing compliance, increasing audit rates may be more effective than increasing penalty rates. However, the former is costlier and more difficult than the latter. Because of this, it might be tempting to use a combination of high penalty rates with low audit rates to discourage evasion.[12] Yet, this combination, as Sandmo (2005) pointed out, "might lead to unacceptable high penalties for a few for violations committed by many."[13]

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[11] The authors explain this observation with the provision of "public goods" in the experiment. These "public goods" were provided by increasing the collected taxes by some multiple, first, and then dividing the resulting amount equally among the participants (Alm, McClelland, et al., 1992).

[12] This is the case in the US, where audit rates are substantially lower than the penalty rate for tax fraud.

[13] Sandmo (2005) calls this argument a "horizontal equity argument".

Extensions of the Neoclassical Model

There are many extensions of the basic A-S model. The ones which are most relevant to the scope of the dissertation will be discussed in this section.[14] Some of the theoretical conclusions derived from these extensions will also be empirically tested in the following chapters.

The basic model described above assumes a constant probability of detection that is independent of the amount of the declared income. Allingham and Sandmo (1972) extended this model to include varying probabilities of detection. In this extended model, this probability is a function of the declared income, $p(X)$. The key assumption of this model is that the higher the amount of the declared income is, the lower is the probability, i.e., $p'(X) < 0$. This assumption is reasonable for the low-income brackets in the US. The audit rates are higher for the US taxpayers who report no adjusted gross income than their compatriots who declared some small amount of income. Moreover, audit rates are generally a little higher for the low-income brackets than for the middle-income brackets. However, audit rates substantially increase with the adjusted gross income starting from the middle-income brackets (See **Table 1.1**). Thus, while the assumption of $p'(X) < 0$ seems reasonable for taxpayers who declare no income or low income, it may not be justified for middle- and high-income taxpayers in the US.

Table 1.1. Examination Coverage: Individual Income Tax Returns Examined, by Size of Adjusted Gross Income, Fiscal Year 2017

Size of adjusted gross income [1]	Returns filed in Calendar Year 2016 (percentage of total) [2]	Examination coverage in Fiscal Year 2017 (percentage) [3]
All returns [4]	**100.00**	**0.62**
No adjusted gross income [5]	1.69	2.55
$1 under $25,000	36.47	0.71
$25,000 under $50,000	23.33	0.49
$50,000 under $75,000	13.26	0.48
$75,000 under $100,000	8.59	0.45
$100,000 under $200,000	12.19	0.47
$200,000 under $500,000	3.60	0.70
$500,000 under $1,000,000	0.58	1.56
$1,000,000 under $5,000,000	0.26	3.52
$5,000,000 under $10,000,000	0.02	7.95
$10,000,000 or more	0.01	14.52

[1] Adjusted gross income is total income (including losses), as defined by the Internal Revenue Code, less statutory adjustments—primarily business, investment, and certain other deductions.
[2] Calendar Year (CY) 2016 data are presented because, in general, examination activity is associated with returns filed in the previous calendar year. The total number of individual income tax returns filed in CY 2016 was 149,919,416. See table 9a for additional details.
[3] Represents returns examined in Fiscal Year 2017 for each adjusted gross income (AGI) class, as a percentage of the total number of returns filed in Calendar Year 2016 for that

[14] Some other notable extensions, which are outside of this dissertation's scope, are: the A-S model adapted to social welfare of evader and non-evaders (Sandmo, 1981, 2005); the model with rank-dependent expected utility (Bernasconi, 1998); the model of a monopolistic firm evading indirect taxes (Massimo Marrelli, 1984); the model of an oligopolistic firm evading taxes (M. Marrelli & Martina, 1988) and the model extended to late tax payments (Gemmell, 2016).

AGI class.

[4] In addition to examinations of returns filed, the IRS examined more than 62,800 cases in which no return was filed. These nonfiler cases were referred for examination by the Collections Program and the Automated Substitute for Return (ASFR) Program. Under the ASFR Program, the IRS uses information returns from third parties (such as Forms W–2 and 1099) to identify tax return delinquencies, constructs tax returns for certain nonfilers based on that third-party information, and assesses tax, interest, and penalties based on the substitute returns. These nonfiler cases are excluded from the examination data in this table. See Table 14 for information on the ASFR Program.
[5] Includes returns with adjusted gross income of less than zero. AGI may be less than zero when a taxpayer reports losses or statutory adjustments that exceed total income.

SOURCE: Table 9b on p.27 in *the Internal Revenue Service Data Book 2017* (IRS, 2018).

Allingham and Sandmo (1972) also considered a dynamic model of tax evasion. In this model, a taxpayer makes a decision about tax evasion not only once, but in multiple time periods. If she is caught, the tax authority will audit the taxpayer for all previous time periods until the period when the taxpayer was fully compliant. Thus, in this model when making the decision, the taxpayer should consider her actions in the previous periods. This is a more realistic model than the static A-S model, even though the basic structure is the same.

Yitzhaki (1974) developed another important extension of the A-S model. In Yitzhaki's model, the penalty is imposed on the evaded tax and not on the underreported income.[15] The main theoretical conclusion of this extension is that the tax rate is negatively associated with tax evasion.[16] Thus, Yitzhaki's (1974) model suggests that increasing the tax rate will decrease tax evasion, if the penalty is levied on the evaded taxes.

Another interesting extension of the A-S model considers earnings from black market work (Sandmo, 1981, 2005). This extension combines a standard labor-supply model with the A-S model. The main idea of this hybrid model is that a taxpayer can decide about evasion not only while filing taxes, but also at the time when she provides labor in a black market. While the comparative static analysis of this model is quite complicated, its general theoretical conclusions are similar to those of the A-S model.

A crucial element missing from the basic A-S model is the provision of public goods and services financed through taxes. Kolm (1973) suggests that when deciding whether to cheat on taxes or not, a taxpayer also considers utilities derived from public goods and services. Kolm (1973) extends the A-S model by adding a utility function for public goods, V, to the expected utility function (1). This utility function for public goods is a function of the "net average [tax] revenue", T, which Kolm (1973) defines as average taxes and expected penalties collected, $R(=\theta X + p\pi(W-X))$, minus the average audit costs, $C(p)$.[17] Thus, according to Kolm's model, a representative taxpayer has the following expected utility function:

[15] As was already mentioned, such penalty system is practiced in countries like the US, Israel and Switzerland.

[16] Gahramanov (2009) further extended Yitzhaki's theoretical results. For more details, see his *The Theoretical Analysis of Income Tax Evasion: Revisited* (Gahramanov, 2009).

[17] Note that $C(p)$ is a function of the probability of detection, p.

$$S = E[U] + V(T) = (1-p)U(W-\theta X) + pU\big(W-\theta X-\pi(W-X)\big) + V(\theta X + p\pi(W-X) - C(p)).$$

Kolm (1973) recognizes that to a single taxpayer T is given (since the number of taxpayers is very large) and, therefore, a single taxpayer will maximize only $E[U]$. He suggests that government should set θ, π and p so as to maximize S (Kolm, 1973). Hence, Kolm alludes to the fact that what is optimal for a single taxpayer may not be so for the entire society. This suggestion also assumes that the government should act as a social planner and maximize taxpayers' utility. Yet, in reality, it is hard, if not impossible, to define everyone's utility function, and the government (or the tax authority) may use goals which are more measurable. For example, these goals can be maximizing net revenues or maximizing compliance. Depending on these goals, the "optimal" values of θ, π and p can be different.

To address a taxpayer's social and moral considerations, the basic A-S model was also extended to include variables representing social stigma (Allingham & Sandmo, 1972) or "disutility" derived from evading taxes (Sandmo, 2005). Allingham and Sandmo (1972) refer to these variables as "nonpecuniary factors in the taxpayer's decision on whether or not to evade taxes". The next chapters will focus on some of these "nonpecuniary factors". In his Nobel lecture, Richard Thaler (2017) called them "supposedly irrelevant factors" – behavioral factors that are not usually deemed to be important in standard economic theory. Before discussing these factors, I will briefly review the main shortcomings of the A-S model. Most of these shortcomings stem from the fact that the model largely ignores the "supposedly irrelevant factors".

Criticism of the Allingham-Sandmo Model

While an elegant tool for theoretical analysis, the A-S model has some conceptual and practical limitations, which will be discussed in this section. A key problem lies in the assumption that a taxpayer is capable of calculating her expected utility function and that she maximizes it by selecting the optimal value of X – the declared income. This assumption is problematic because optimizing this expected utility function can be an extremely difficult, if not impossible, task even for a seasoned economist. To accomplish this task successfully, one needs to know the following key elements of the model: U – utility function and its functional form; p – probability of detection; π – penalty rate; and θ – tax rate. Each of these elements has complications that can stymie the task.

First, most taxpayers are unlikely to know what utility functions are. Those who do still have to know the specific mathematical form of their utility function (or at the very least, the relationship between their utility and income) in order to solve for the optimal value of X. Specifying the "true" or even an "approximated" functional form is not a trivial task. Even determining general characteristics of a utility function like risk aversion may not be easy. After all, how many taxpayers (including, those who are economists) can specify their own utility functions that would accurately reflect their own preferences with respect to their income? And how many actually do that?

Second, there are several problems associated with the probability of detection, p, from the model. To begin with, some people may not fully understand the concept of probability and have difficulties evaluating the risks. A taxpayer who is proficient in probability theory still needs to estimate the probability of detection. To estimate it, she would first need to compute her probability of being audited (or her return to be reviewed). This taxpayer may be able to come up with reasonable estimates of the audit probability based on the publicly available historical data. However, to calculate the probability of detection, she also needs to know how effective the auditors are in detecting evasion, and to the extent this information exists, it is not easily accessible to the general public. Furthermore, the detection effectiveness is likely to vary by different income sources. Consequently, if the taxpayer has income from different sources, she will also have to calculate the probability of detection for each type of income. Additionally, the probability of detection may be correlated with reported income (which seems to be the case in the US). This will add another layer of computational complexity. Finally, calculating the probability of detection becomes even more complicated, when tax authorities can audit previous years if a taxpayer is caught underreporting. In this case, the probability of detection in a certain year will not be independent of the taxpayer's actions in prior years. This will require estimating probabilities for each year conditional on the taxpayer's decisions in the other years.

Instead of conducting the abovementioned calculations, taxpayers may often rely on "intuition" and use subjective probabilities. While this approach is an easier solution to the problems discussed in the previous paragraph, it is susceptible to different biases. There is evidence suggesting that people are subject to systematic biases when they evaluate probabilities. For example, they tend to overweight small probabilities and underweight large probabilities (Camerer & Ho, 1994; Gonzalez & Wu, 1999; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Wu & Gonzalez, 1996). Taxpayers also seem to underestimate the audit probability when they were audited in the preceding period (Maciejovsky et al., 2007; Mittone, 2006).[18] Because of such biases, the A-S model may yield suboptimal values of declared income, X.

Third, the A-S model assumes that taxpayers are fully informed about penalties for tax evasion. This may not be the case for many taxpayers. Even the developers of the model, Allingham and Sandmo (1972) acknowledge that "…the penalty rate … may itself be uncertain from the point

[18] Some lab experiments show that tax compliance sharply declines in the period immediately following the period where taxpayers were audited (Guala & Mittone, 2005; Maciejovsky et al., 2007; Mittone, 2006). Mittone (2006) calls this phenomenon the "bomb crater effect". To explain the origin of this term, he writes: "The term derives from the First World War: during bombardments, soldiers would take shelter in bomb craters in the belief that it was impossible for a bomb to fall in the same place twice." He argues that taxpayers may have similar beliefs about tax audits, and these beliefs may be the reason for the sharp decline in the compliance immediately after an audit. Interestingly, this effect may last for several periods after the audit (Maciejovsky et al., 2007; Mittone, 2006). Mittone (2006) calls this the "echo effect".

of view of the taxpayer." In some countries, this uncertainty may be rooted in the complexity of the penalty structure. For example, in the US, there are several types of civil penalties like failure-to-file penalties, failure-to-pay penalties, combined penalties, accuracy-related penalties and fraud penalties. Besides civil penalties there are also criminal penalties. Additionally, interest rates on evaded taxes may be charged too, not to mention court expenses if a taxpayer is criminally charged for evasion.

The uncertainty about the penalties may also arise from the fact that in some cases they can be waived or abated. For instance, criminal, as well as civil fraud penalties cannot be imposed without satisfactory evidence that tax underpayment is due to fraud. Yet, it is usually difficult to prove that a taxpayer intentionally and willfully underreported the income. Because of this, there is a good chance that a tax evader who got caught may not be prosecuted at all, and only be penalized with fines lesser than fraud penalties.[19] Besides that, there are sometimes tax amnesties during which taxpayers who disclose their previously underreported taxes voluntarily may receive full or partial penalty relief and/or avoid criminal prosecution. Therefore, a taxpayer who makes decision based on the A-S model should also estimate and consider the probability of penalties being enforced.

Fourth, the standard A-S model assumes that the tax rate is constant and is known to taxpayers. However, given that individual income taxes are frequently used as an income re-distribution tool, tax rates vary by income level in most of the countries in the world.[20] Such variation substantially complicates the model since the overall tax rate becomes a function of declared income. Furthermore, having multiple rates is likely to make taxpayers less informed about their effective tax rates.

Given the complexities discussed above, it is extremely unlikely that taxpayers use anything like the A-S model to make decisions about how much income to declare to tax authorities. Even if they conduct some sort of analysis on whether to underreport or not, they probably employ "rules of thumb", guesstimates and other heuristics for it. Indeed, taxpayers' decision-making processes have the attributes of a classic "bounded rationality" case, when individuals make decisions based on heuristics, instead of rigorous mathematical optimization rules. Herbert Simon, who coined the term "bounded rationality", suggests that individuals may act this way under certain conditions when there are "failures of knowing all the alternatives, uncertainty about relevant exogenous events, and inability to calculate consequences" (Simon, 1979). All these circumstances exist in the context of tax evasion. A typical taxpayer may not know about all available alternatives (e.g. legal loopholes, tax deductions, tax credits etc.) that can reduce

[19] Difficulty of obtaining evidence of fraudulent tax underpayment may be the reason for very low number of fraud penalties assessed in the US. The number of fraud penalties was only 2,533 out of over 31 million total civil penalties assessed for individual, estate and trust income in 2017 FY (IRS, 2018). The number tax related criminal investigations in the same year was low too, by being little over 3,000 (IRS, 2018). Moreover, not all of these investigations were referred to prosecution, and substantial number of them were not related to tax evasion.

[20] Less than 40 of the existing and recognized countries have or had flat tax systems.

her tax burden. There are also uncertainties about "relevant exogenous events" like audits, detection of evasion and penalty enforcement. And the computational complications described above can easily make a taxpayer unable to calculate consequences of non-compliance.

How useful is this model to policy makers then?

As a policy analysis tool, it has its limitations. First*, the model and its extensions mostly focus on only three policy levers: p – the probability of detection, π – penalty rate, and θ – tax rate*. While the model provides unambiguous and empirically supported predictions for p and π , its predictions regarding θ, as well as actual income, W, are less certain. For example, the standard A-S model cannot unambiguously predict what would happen to the level of underreporting when the tax rate is changed. Moreover, as discussed earlier, these predictions about the impact of the tax rate on evasion, even when theoretically unambiguous, are not always confirmed by empirical studies.

Second, *the model only describes tax evasion and does not easily extend to the other types of non-compliance* like tax avoidance. Tax avoidance can be as big of a problem or even a bigger policy problem than tax evasion. However, the structure of the A-S model makes it very difficult to consider this policy issue within the model.

Third, *the model largely ignores interactions between taxpayers and tax authorities, as well as other agents like tax preparers, media, taxpayers' social network and government organizations providing public goods and services*. These interactions directly and/or indirectly affect tax compliance. For example, there seems to be a complex change in compliance behavior, which is termed "bomb crater" effect, after taxpayers are audited (Guala & Mittone, 2005; Maciejovsky et al., 2007; Mittone, 2006). Besides audits, tax authorities often communicate with individual taxpayers by sending them different kinds of letters and notifications like reminder letters, requests for information and math error notices. Through several randomized field experiments conducted in different countries, it is known that this communication and its content can influence compliance behavior as well (Bott, Cappelen, Sørensen, & Tungodden, 2017; Hallsworth, List, Metcalfe, & Vlaev, 2017; Kleven, Knudsen, Kreiner, Pedersen, & Saez, 2011; Slemrod, Blumenthal, & Christian, 2001). Tax amnesty programs are another example of interaction between tax authorities and taxpayers. While these programs usually do not have long-term positive impact on tax compliance, they can sometimes be successful in raising tax revenues in the short run (Alm et al., 1990; Alm & Rath, 1998).

Interaction with other government agencies that provide public goods and services may also affect taxpayers' decision to be tax compliant. At the very least, provision of public goods seems to be usually associated with higher compliance (Alm, Jackson, et al., 1992; Alm et al., 1990), especially when taxpayers perceive that the others pay their share of taxes too (Alm, Jackson, et al., 1992). Moreover, there is some empirical and experimental evidence suggesting that taxpayers can be more compliant when they are able to influence decision on how their taxes are spent (Alm et al., 1993; Lamberton, De Neve, & Norton Michael, 2017; Pommerehne & Weck-Hannemann, 1996). They are also likely to be compliant if they are satisfied with the public programs that their taxes fund (Alm et al., 1993).[21] Nevertheless, there is some evidence for "free-riding" behavior too (Park & Hyun, 2003).

Taxpayers' behavior is also influenced by media coverage of tax issues and tax authorities (Battiston, Duncan, Gamba, & Santoro, 2016; Kasper, Kogler, & Kirchler, 2015), as well as taxpayers' social network (Alm et al., 2017; Alm, Jackson, & McKee, 2009). However, as was already stated, these and the abovementioned interactions are not reflected in the standard A-S model. By disregarding them, one is bound to overlook some policy opportunities available to improve compliance.

Fourth, *fairness, equity and justice aspects of tax systems are beyond the A-S model's scope*. These aspects are often considered (or at least, should be) while designing tax policies. Fairness, equity and justice are usually one of the key considerations in addressing questions like: Who should pay taxes? How much taxes they should pay? How tax revenues should be re-distributed and spent? What should be the penalty for non-compliance? These issues are not only important to policy makers, but also to taxpayers. Taxpayers seem to be concerned with fairness of taxes too (Braithwaite, 2003; Hartner, Rechberger, Kirchler, & Schabmann, 2008; Rawlings, 2003; van Dijke & Verboon, 2010).[22] Admittedly, taxpayers' fairness, equity and justice considerations can be squeezed into "nonpecuniary factors" variable of the A-S model. Still, they have not been addressed in the model explicitly.

Finally, *since taxpayers are unlikely to use this model explicitly to make their decision, it provides limited understanding on a range of factors involved in taxpayer behavior*. *Hence, it offers only few ideas to policy-makers on how to respond to tax evasion.* The model assumes that taxpayers make decisions to maximize their utility, whereas taxpayers may comply or evade for reasons other than that. It does not consider heuristics that taxpayers use or may use while making decision about being compliant or not. It also does not reflect the fact that taxpayers' behavior is frequently subject to numerous biases, misperceptions, misinformation and various other factors. Studying all these heuristics, biases and factors can help to determine a range of policy interventions for improving tax compliance. Some of these behavioral factors will be examined in the next chapters.

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[21] It should be noted that, to some extent, satisfaction with public goods and services is addressed by Kolm's (1973) extension of the A-S model.

[22] Kirchler (2007) provides a good detailed discussion of fairness, equity and justice issues in the context of tax compliance in his book *The Economic Psychology of Tax Behavior* (see pages 73-96).

Concluding Remarks

So how good is the A-S model as an economic model? It is a simple and elegant model that allows one to think about a tax evader's decision-making process in a structured way. While being simple, it has capacity for being easily extended to include many real-world complexities. Some of these extensions have already been discussed above.

Besides elegance and ability to depict complexities, economic models are also verified in terms of their predictive power and reasonableness of their key assumptions.[23] As was discussed in this chapter, the model has limited predictive power. While some of its theoretical predictions are certain and empirically supported, others are ambiguous and/or contradictory to real-life situations. Furthermore, the model is mostly focusing on penalty rate and probability of detection, and largely ignores other important factors that likely affect tax behavior. Because of these shortcomings, the model provides limited guidance for policy-makers.

The A-S model is also based on some disputable assumptions. One of these assumptions is that taxpayers are fully informed about the objective characteristics of the tax system like penalties, probability of detection and tax rates. The predictive power of the model is probably highest in a situation where professional tax preparers do the taxes for an individual or a company, but is likely less useful for understanding how regular citizens make tax decisions, and how they can be induced to report their taxes more truthfully. In the next chapters, I will empirically test the key assumption of rationality of the taxpayer (as most empirical evidence does not test the assumption directly but infers it from observed behavior) and will explore to what extent individual perceptions of penalty, audit and tax rates reflect their objective counterparts.

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[23] For a good summary of how economic models are evaluated, see *Verification of Economic Models* section of Chapter 1 in *Microeconomic Theory: Basic Principles and Extensions* by Walter Nicholson (Nicholson, 2005).

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Chapter 2: Biases in Perception of Audit, Penalty and Effective Tax Rates

Introduction

As was already mentioned in the previous chapter, the Allingham-Sandmo (A-S) model presumes that by maximizing their expected utility function, taxpayers decide if and by how much they should evade taxes (Allingham & Sandmo, 1972). This function depends on exogenous parameters like the probability of detection, tax rates and penalties, and in the model, it is assumed that taxpayers are well-informed about them. In this chapter, this assumption is tested with novel empirical data from the American Life Panel Tax Evasion Survey. The data allows to explore the following specific research questions:

- How do individual perceptions of audit rates, penalty rates and effective tax rates correspond to the actual values of these rates? If there are any misperceptions or biases, how large are they?
- What personal characteristics, experiences, attitudes and beliefs are associated with these misperceptions and biases, if there are any? Are there certain groups of taxpayers who are more susceptible to these misperceptions?

The current chapter addresses these questions and provides empirical evidence that there are sizable gaps between taxpayers' perceptions and the actual values of the audit, tax and penalty rates in the US. Some plausible explanations for these perception gaps are considered and discussed as well. The chapter also provides profiles of people who are susceptible to these misperceptions and biases. These profiles, as well as overall findings of this chapter, can help policy makers develop targeted and better-informed tax compliance policies.

The chapter starts with a brief description of the data and the methods used in the analyses. Next follows a section with the descriptive analyses of the misperceptions related to the audit, penalty and tax rates. This section also provides estimates for the magnitudes of these misperceptions. The next section presents regression analyses of the perceived audit, penalty and tax rates. I conclude the chapter discussing theoretical and practical implications of the findings, as well as the limitations of the analyses.

Data and Methods

Data

This chapter uses data from the RAND Corporation's American Life Panel (ALP)[24] Tax Evasion Survey, a nationally representative survey of 1029[25] U.S. adults. The survey was fielded between July 14th and September 2nd, 2016, as part of a project funded by the National Science Foundation (NSF).[26] The survey dataset[27] contains various self-reported variables for perceptions related to tax evasion, demographic and social network characteristics, personal experiences with and attitudes toward the U.S. tax system. Among them, the main three variables of interest are perceived audit rate, perceived penalty rate and perceived effective tax rate. The survey questions for these three variables are reproduced verbatim below:[28]

> ***Perceived Audit Rate:*** *"The following questions ask about your thoughts and experiences regarding US federal income taxes. Specifically, they ask you about three aspects of how income taxes work:*
>
> - *The audit rate: The percentage of taxpayers whose returns are audited by the IRS,*
> - *The penalty rate: The size of the penalty for not paying all of your owed taxes, and*
> - *The effective income tax rate: The percentage of your income that you owe to the government in taxes.*
>
> *First let's consider the audit rate.*
>
> *In a typical year, what percent of taxpayers in the U.S. will have their income tax return audited by the IRS?"* Range: 0.0..100.0

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24 The RAND American Life Panel (ALP) is a nationally representative, probability-based panel of over 6,000 members. The panel consists of individuals who are 18 and older. The panel members are regularly interviewed over the internet for research purposes. They are provided with the technology to respond to surveys online. Thus, the panel also includes respondents who would have not had access to the internet otherwise. The panel is longitudinal, which allows tracking responses from the same participants over the time and across different surveys administered to them. Since January 2006, ALP has fielded over 500 surveys on topics such as financial decision making, health behavior and outcomes, retirement decisions, inflation expectations, political attitudes related to the presidential elections, working conditions, and more.

25 Thirteen hundred and twenty people were invited to participate in this survey. About 78% (1029) of these invitees took the survey.

26 This was *An Agent-Based Model of the Role of Income Tax Evasion Perceptions* project funded by the National Science Foundation's Interdisciplinary Behavioral and Social Science (IBSS) Research program. Award Number 1519116.

27 It is publicly available and can be downloaded free of charge from https://alpdata.rand.org/. The survey number is 456.

28 The entire questionnaire can be found in **Appendix A**. It can also be downloaded from https://alpdata.rand.org/.

Perceived Penalty Rate: *"Now let's consider the penalty rate. If the IRS detects that a person has underreported their taxes, they will first have to pay the unpaid taxes that were due. In addition, they will be assessed a penalty that is a percentage of the amount they underpaid. This percentage is the penalty rate. Imagine a person was caught underpaying their taxes by $1000. In addition to having to pay that $1000, how much of a penalty would they have to pay? (Please enter this as a dollar amount. Do not use commas.)"*

Perceived Tax Rate: *"Now let's consider the effective income tax rate. This is the percent of your income that you owe in taxes to the federal government each year. What do you think your effective income tax rate was this past year?"* Range: 0.0..100.0[29]

The responses to these questions were converted into decimals or percentages before conducting the analysis of this chapter.

For comparison with these responses, the actual values for the audit, penalty and tax rates were taken from publicly accessible IRS publications. The actual audit rates (shown in **Table 2.1**) were usually below 1% in the five years preceding the survey year (IRS, 2013, 2014, 2015, 2016, 2017a). A simple average of these rates was 0.88%.

Table 2.1: Percent of Individual Income Tax Returns Examined (2011-2015 Calendar Years).

Calendar Years	Examination Coverage (percent)*
2011	1.03
2012	0.96
2013	0.86
2014	0.84
2015	0.70
Average	***0.878***

NOTE: * - This shows the percent of individual income tax returns that was filed in a given calendar year (CY) and examined in the next fiscal year (FY). For example, out of all returns filed in CY 2012 only 0.96% was examined in FY2013.
SOURCE: Table 9b in the IRS Data Books for 2012-2016

Unlike the audit rate, obtaining the actual penalty rate was less straightforward. The problem is that different penalty rates, or even a combination of penalty rates and types, may be applied under different circumstances. While acknowledging wide variety of possible circumstances, this chapter considered only three scenarios that were most relevant to the perceived-penalty-rate question and its context. The scenarios and their corresponding penalty rates have been summarized in the table below. They are based on the author's personal interpretations of the

[29] Note that the question is about federal income tax.

"Penalties" section in Chapter 1: "Filing Information" of *Publication 17: Tax Guide 2017 for individuals* (pages 18-20) (IRS, 2017d).

Table 2.2: Typical Penalty Rates under Different Scenarios

Scenario	Penalty Type	Penalty Rate
A person filed a return and underpaid tax on the return due to fraud. The authorities have strong evidence for it.	Fraud	75%
A person filed a return and the underpayment is because the person claimed tax benefits for a transaction that lacks economic substance or he/she failed to disclose a foreign financial asset.	Higher Rate of Accuracy-related Penalty	40%
A person filed a return, but the tax underpayment is due to negligence or disregard of rules and regulations, and/or $1,000 is more than 10% of the correct tax (substantial understatement of income tax).	Accuracy-related Penalty (typical case)	20%

SOURCE: Based on own personal interpretations of "Penalties" section in Chapter 1: "Filing Information" of *Publication 17: Tax Guide 2017 for individuals*, pages 18-20.

The highest penalty rate among these three cases is 75%. This rate is applied when an underpayment of taxes is due to fraud. However, this penalty is rarely used. As was already mentioned in Chapter 1, the number of fraud penalties was only 2,533 out of over 31 million total civil penalties assessed (0.01%) for individual, estate and trust income in 2017 FY (IRS, 2018). Similarly small relative numbers of fraud-penalty cases were observed in other years too (IRS, 2015, 2016, 2017a). This is in part because the tax authorities have the burden of proving a fraud case and it is usually very difficult to obtain a convincing evidence for a fraudulent underpayment of taxes. More common than the fraud penalty is the accuracy-related penalty. The highest accuracy-related penalty rate is 40%. The typical rate is 20%, according to some tax researchers like Andreoni, Erard, and Feinstein (1998). [30] They write:

> *"U.S. taxpayers who understate their tax liabilities may be subjected to civil or criminal penalties. Typically, civil penalties are applied at a rate of 20 percent of the portion of the underpayment of tax resulting from a specified misconduct (negligence, substantial understatement, substantial valuation misstatement, etc.). However, in cases of fraud, which involve clear and convincing evidence that the*

[30] In a personal communication, Dr. Kim Bloomquist, a retired Senior Economist with the U.S. IRS Office of Research, also wrote: "It would not be unreasonable to just assume a 20% rate [*for a typical penalty rate*] based on the question [*about the perceived penalty rate*] asked on the [*ALP Tax Evasion*] survey." (K.Bloomquist, email, April 4, 2018).

taxpayer engaged in intentional wrongdoing, a civil penalty may be applied at a rate of 75 percent"(Andreoni et al., 1998).

For the sake of simplicity, only statutory penalty rates were considered. But it should be acknowledged that for a person, actual economic costs of being caught underpaying taxes may be higher than just the penalties.[31] For instance, if the taxpayer borrows money to pay the fines, then the interests paid on the borrowed amount will be additional costs for her. In addition, legal costs and fees may be incurred if the taxpayer decides to hire legal or professional help to deal with the problem.

The estimates used as the actual effective federal income tax rates are presented in **Table 2.3**. These estimates were assigned to each respondent in accordance with their reported family income. As an example, if a respondent reported family income to be between $30,000 and $39,999, then her "actual" effective tax rate was marked as 4.8%, which is the estimated average effective tax rate for that income group.

Table 2.3: Estimated Average Effective Federal Income Tax Rates by Household Income Brackets

Household Income	Estimated Average Effective Tax Rate
less than $5,000	-0.2%
$5,000 to $9,999	0.4%
$10,000 to $14,999	0.9%
$15,000 to $19,999	1.8%
$20,000 to $24,999	2.8%
$25,000 to $29,999	3.6%
$30,000 to $39,999	4.8%
$40,000 to $49,999	6.2%
$50,000 to $74,999	8.1%
$75,000 to $99,999	9.5%
$100,000 to $199,999	12.6%
$200,000 or more	23.8%
Overall	**14.3%**

SOURCE: Own calculations based on the data in Table 1.1 for Tax Year 2015 in Publication 1304, Statistics of Income Division, IRS, September 2017:
https://www.irs.gov/statistics/soi-tax-stats-individual-statistical-tables-by-size-of-adjusted-gross-income#_grp1 [Last accessed on 9/05/2018]

These average effective tax rates were calculated based on *Table 1.1: All Returns: Selected Income and Tax Items, by Size and Accumulated Size of Adjusted Gross Income, Tax Year 2015*

[31] I am thankful to Dr. Kim Bloomquist for pointing out that the actual economic costs of being caught underpaying taxes might be different from the statutory penalties.

(Filing Year 2016) from IRS' Statistics of Income (SOI) Tax Statistics, Individual Complete Report, Publication 1304. This table has the amount of total adjusted gross income less deficit (column 3 in the table) and the total amount of income tax (column 16) by different income brackets (see **Appendix B**). For each income bracket, the total income tax was divided by the total adjusted gross income to obtain the average effective tax rates. As an illustration, the total adjusted gross income less deficit was $519,525,813 thousand for the income bracket of $30,000-$40,000, and the total income tax for that income group was $25,167,676 thousand. Dividing the latter number by the former results in 4.8% (= $25,167,676 thousand/$519,525,813 thousand), which is the average effective tax rate for that income group in **Table 2.3**. All the other rates in **Table 2.3** were estimated the same way.

The highest marginal tax rate was also estimated for each respondent. Two key variables: the respondents' reported family income and their marital status were used to estimate these rates. These estimates can be found in **Table 2.4**.

Table 2.4: Estimated Marginal Federal Income Tax Rates for the Tax Evasion Survey Respondents by Family Income and Marital Status

The ALP Income Brackets*	Married		Single (Separated, Divorced, Widowed, and Never Married)		Total number of respondents
	Number of Respondents	Estimated Marginal Tax Rate	Number of Respondents	Estimated Marginal Tax Rate	
< $5,000	4	0%	11	0%	15
$5,000 to $7,499	5	0%	10	0%	15
$7,500 to $9,999	2	0%	20	0%	22
$10,000 to $12,499	5	0%	9	10%	14
$12,500 to $14,999	1	0%	15	10%	16
$15,000 to $19,999	13	0%	40	10%	53
$20,000 to $24,999	22	10%	28	15%	50
$25,000 to $29,999	21	10%	27	15%	48
$30,000 to $34,999	22	10%	33	15%	55
$35,000 to $39,999	18	10%	28	15%	46
$40,000 to $49,999	34	15%	32	15%	66
$50,000 to $59,999	39	15%	29	25%	68
$60,000 to $74,999	56	15%	27	25%	83
$75,000 to $99,999	88	15%	32	25%	120
$100,000 to $124,999	108	25%	14	28%	122
$125,000 to $199,999	73	25%-28%	16	28%	89
$200,000 and more	48	28%	5	33%	53

NOTE: * - The respondents had to pick one of these income brackets when answering the family income question: "*Which category represents the total combined income of all members of <u>your family</u> (living here) during the past 12 months? This includes money from jobs, net income from business, farm or rent,*

pensions, dividends, interest, social security payments and any other money income received by members of your family who are 15 years of age or older"
SOURCE: Own calculations based on the ALP Tax Evasion Survey data and the information on marginal tax rates in *Section 3: Individual Income Tax Rates* of *Statistics of Income -2015: Individual Income Tax Returns, IRS Publication 1304.*

Several assumptions were made to estimate these marginal tax rates. These assumptions are the following: 1) The reported family income was assumed to be equal to the adjusted gross income, which is defined as "total income less statutory adjustments to income (e.g., deductible contributions to an IRA or Keogh plan)" (IRS, 2017b). 2) The filing status was assumed to be "Married and Filing Jointly" for all respondents who indicated that they were married or living with a partner filed their tax return, and "Single" for all the other respondents. 3) It was assumed that the respondents claimed ***only*** the standard deductions ($6,300) and the personalized exemptions ($4,000). Thus, for the "single" (unmarried) respondents the taxable income was equal to the reported family income minus $10,300 (=$6,300 + $4,000). For the married respondents, $20,600 (=2*$10,300) was subtracted from the reported family income to estimate taxable income. 4) For married respondents with income from $125,000 to $199,999, there were two possible marginal tax rates 25% and 28%. Since for these respondents the exact amount of the family income was not available, the midpoint of these two rates, 26.5%, was used as the estimate of the highest marginal tax rate. 5) The marginal tax rate was assumed to be 28% for all married respondents with family income of $200,000 and above. 6) The marginal tax rate was assumed to be 33% for all "single" (unmarried) respondents with family income of $200,000 and above. While these assumptions may not be feasible for certain individual respondents, overall, they are not unreasonable. Besides, given the limitations of the available data, it would have been impossible to estimate the marginal rates without making these assumptions.

Methods

Individual responses for perceived audit rates, penalty rates and effective tax rates were compared to the estimates of actual rates. The following differences between perceived and actual rates were calculated for each respondent:

$$\boldsymbol{A_i - \bar{A}}$$

$$\boldsymbol{P_i - \bar{P}}$$

$$\boldsymbol{T_i - \bar{T}_i}$$

where $\boldsymbol{A_i}$ is the i^{th} respondent's perceived audit rate; $\boldsymbol{\bar{A}}$ is the percentage of individual income tax returns examined in a typical year; $\boldsymbol{P_i}$ is the i^{th} respondent's perceived penalty rate; $\boldsymbol{\bar{P}}$ is the typically enforced penalty rate; $\boldsymbol{T_i}$ is the i^{th} respondent's perceived effective federal income tax rate; and $\boldsymbol{\bar{T}_i}$ is the estimated actual effective federal income tax rate for the i^{th} respondent.

These differences yielded reasonable estimates of by how much individuals over- or underestimate actual audit rates, penalties for underreporting and effective tax rates.

Overall average of these differences, as well as their distribution were also examined. In the absence of any perception biases, one would expect these differences to be equal to zero, on average. To test this hypothesis, t-test for the mean or one-sample sign test for the median were conducted, as appropriate. Besides these tests, Pearson's, Spearman's and Kendall's correlation coefficients were calculated to see if there is any association between perceived and estimated effective tax rates, as well as between perceived effective and estimated marginal tax rates.

A series of regression analyses were performed to analyze how these perceptions are related to the respondents' personal and social network characteristics, personal experiences with the tax system, their attitudes and beliefs. These, among other things, included age, gender, education, audit experience, employment status (i.e. self-employed or not), attitudes toward tax fairness and public goods and services, whether a respondent talks about taxes with his/her alters or not, and whether a respondent uses services of paid tax return preparers or not. They served as the independent variables in the regression models, while the perceptions of the audit, penalty and tax rates were the dependent variables.

Depending on the specific purpose of the analysis, as well as on the distribution and type of the dependent variable, different types and specifications of regression models were used, such as linear regression models, fractional response models, the generalized linear models, logit, multinomial logit and absolute difference models. The variety of the models also helped to check how robust the results were across different specifications.

Misperceptions and Their Magnitudes

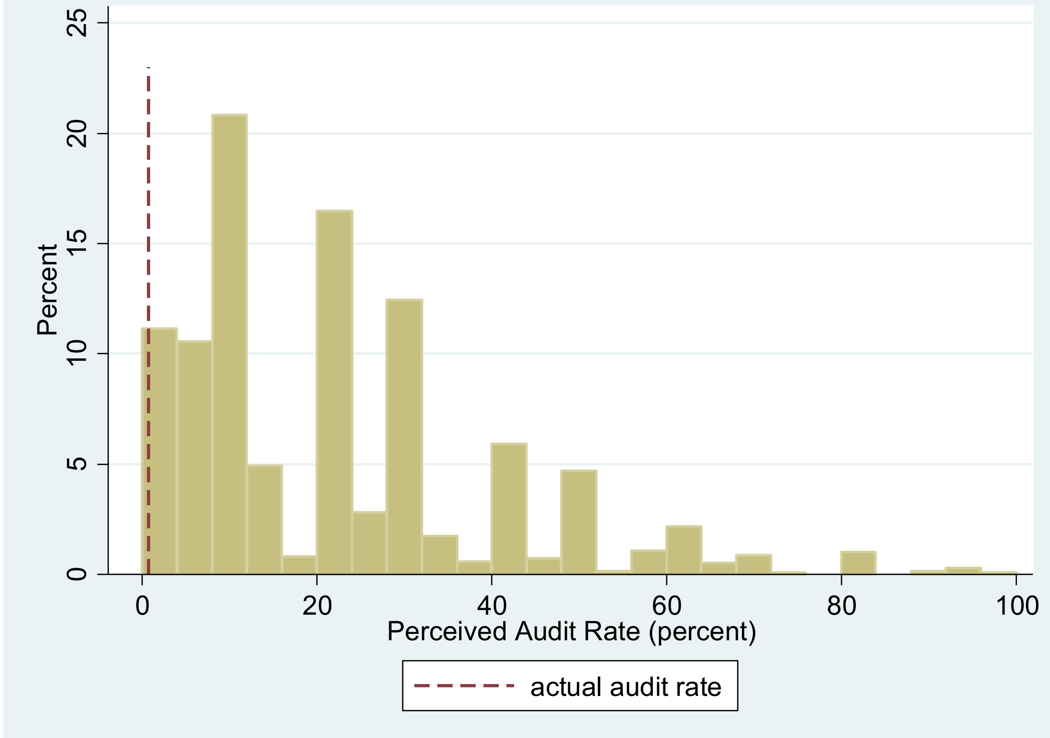
The empirical evidence presented in this section demonstrates that U.S. population are generally not well-informed about the audit, penalty and tax rates, which are the most important key elements of the classical economic model of tax evasion. The evidence related to each one of these elements will be separately considered next.

The Audit Rate

As evident from **Figure 2.1**, most people in the U.S. overestimate the audit rate, when asked: "*In a typical year, what percent of taxpayers in the U.S. will have their income tax return audited by the IRS?*". Only about 4% of the respondents stated that the rate was either 1.5% or less, which are reasonable estimates given the audit rates in the previous five years as shown in **Table 2.1**. The median value for the perceived audit rate is 15% among the respondents. This value is even higher, 20%, when sampling weights are used to estimate the median for the U.S.

population. Even the lowest quartile of perceived audit rate (8% for the respondents, 10% for the U.S. population) is substantially higher than the actual rate.

Figure 2.1: Distribution of Perceived Audit Rates (weighted) vs. The Actual Audit Rate



As shown in **Table 2.5**, the average magnitude of the overestimation is significant, both statistically and practically. On average, the US population overpredicts the audit rate by about 23 percentage points. The estimated 95% confidence interval for the average overprediction is [20.6; 25.3].

Table 2.5: Magnitude of the Misperception for the Audit Rate (one sample t-test)

Sample	Actual Audit Rate	Average Difference (Perceived - Actual)	Standard Error	t-statistic	p-value	95% C.I.
All (n = 1,012)	**0.70% (for CY 2015)**	22.9	1.20	19.2	<0.001	[20.6; 25.3]
	0.878% (average for CY 2011-2015)	22.7	1.20	19.0	<0.001	[20.4; 25.1]
Only those who prepare their tax returns themselves (n = 406)	**0.70% (for CY 2015)**	17.2	1.69	10.2	<0.001	[13.9; 20.5]
	0.878% (average for CY 2011-2015)	17.0	1.69	10.11	<0.001	[13.7; 20.4]

This overprediction is consistent with the empirical findings that people tend to systematically overweight small probabilities (Camerer & Ho, 1994; Gonzalez & Wu, 1999; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Wu & Gonzalez, 1996). Above and beyond this systematic bias, the overestimation of the audit rate might also be partially due to misunderstanding by some respondents of what a tax audit is. For example, they may misinterpret simple checks of tax returns against third-party information or various notifications sent by the IRS as an audit. These checks and notifications are certainly more frequent than tax audits.

Another source of the misperception could be rational inattention to the audit rates. Some people may rationally choose not to know what the audit rates are, if they do not need that information. They could be people who do not have the opportunity or willingness to cheat on their tax returns. They could also be individuals who are not required to file tax returns or who have somebody else prepare their tax returns for them. To such individuals, the knowledge of the audit, the penalty and even, in some cases, the tax rates may be irrelevant and useless. They are likely to be less informed about the rates and, therefore, provide inaccurate estimates.

Indeed, the data suggests that such rational inattention may contribute to the overestimation. The average magnitude of the overestimation decreased after removing from the sample people who have not filed tax returns or who do not usually prepare their tax returns themselves. (Compare the last two rows with the first two rows in **Table 2.5**). Nonetheless, even individuals who prepare their tax returns themselves substantially overestimate the audit rate. They overestimate the rate by over 17 percentage points, on average. Furthermore, less than 8% of them believe that the audit rate is equal to or less than 1.5%.[32] Thus, rational inattention may explain the overestimation of the audit rate only partially.

The Penalty Rates

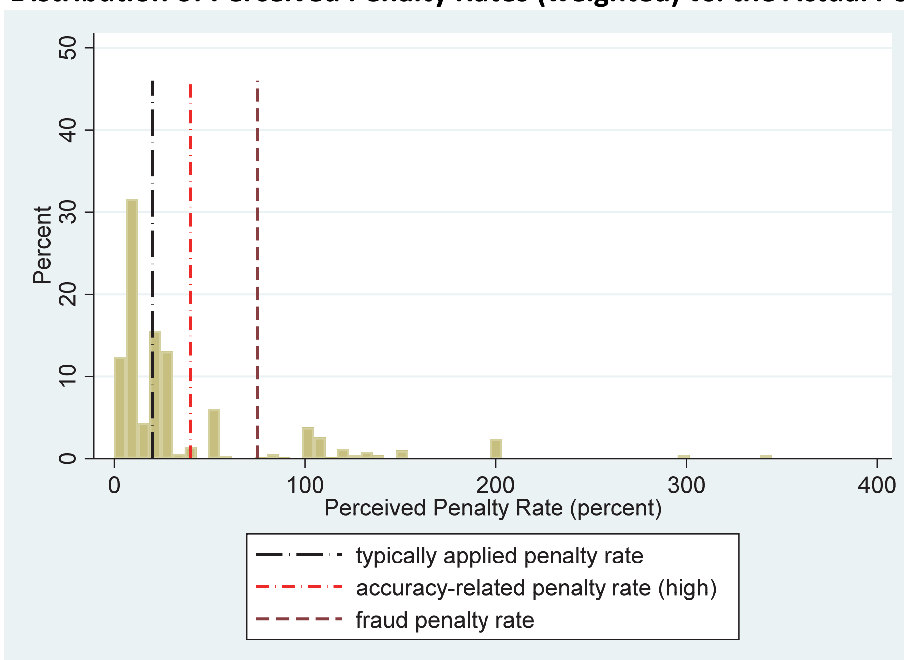
The overall US population also has misperceptions of the penalty rates. However, unlike the audit rate, while there are some who substantially overestimate the penalty rates, large number of people underestimate the rates. The most common (modal) perception about the penalty rate is that it is 10%, which is substantially below the range of the actual rates as shown in **Table 2.2**. Almost 30% of the ALP Tax Evasion survey respondents had this perception. An estimated 26% of the US population share the same belief. The median perceived penalty rate was 15% among the respondents and estimated to be 20% among the population. Only a small fraction of people pinpoint the correct penalty rates. An estimated 16% of the population believe the penalty rate to be 20% (typically applied penalty rate). For the fraud penalty (75%)

[32] It should be acknowledged that some of those who prepare their tax returns themselves may not have the opportunity and/or willingness to cheat. Still, since they make active decisions about how much income to report and what tax deductions to claim, one might expect them to be more informed about the rates than the rest. The fact that taxpayers who prepare their own returns still overestimate the audit rate by a substantial margin is an indication how difficult it is for taxpayers to accurately assess their probability of being audited.

and higher rate of the accuracy-related penalty (40%), the corresponding percentages of responses are even lower: 0.1% and 1.4% of the population, respectively.

Figure 2.2 below illustrates the distribution of the perceived penalty rates against their objective counterparts. As one can see from the figure, this distribution is significantly skewed to the right. The skewness coefficient is 8.9 and the kurtosis is 109.9. These high numbers are due to few extreme values in the data.[33] There are three respondents who perceived the penalty rate to be 1000% and one respondent answered that the penalty rate can be as high as 1500% (although these values are not shown in the figure, in order to visualize meaningful variation closer to zero).

Figure 2.2: Distribution of Perceived Penalty Rates (weighted) vs. the Actual Penalty Rates



NOTE: There are few extreme values on the right tail. These values are not shown in this histogram.

Because of these outliers, the average perceived penalty rate is considerably higher than the median. It is estimated to be 73.5% for the US population. This average value is slightly below the fraud penalty rate. Yet, is this difference statistically significant or not? Testing the significance of this difference gets complicated due to the severe skewness in the distribution. Because of this skewness, a standard one-sample t-test is not appropriate to test if the population mean of the perceived penalty rate is equal to the actual rate.[34] It is more

[33] Removing these outliers or winsorizing them at 95th percentile significantly reduced both skewness and kurtosis. Still, even the censored data was substantially skewed to the right.

[34] A one sample t-test assumes that the population is normally distributed or, at least, not very skewed. However, this assumption cannot be justified with the available data. Logarithmic and square root transformations of the data reduced skewness, but even after these transformations the normality assumption was far-fetched.

appropriate to use non-parametric alternative to the t-test, for example, a one-sample sign test for a median. This was used to test three different null hypotheses: that the median is equal to or greater than 75% (fraud penalty), 40% (higher rate of the accuracy-related penalty) and 20% (the lower rate of the accuracy-related penalty). The first two hypothesis are clearly rejected (see **Table 2.6**). This suggests that the US population may generally not realize that the penalty rates for underreporting taxes can be as high as 40% or 75%. Just like these two penalty rates, more people underestimate the typically enforced penalty rate of 20%, than overestimate it (compare columns "Below" and "Above" in **Table 2.6**). However, the test conducted with the weighted data[35] does not provide enough evidence to conclude that the median perception is different from or lower than 20%.[36] The test yielded a one-sided p-value of 0.14.[37,38]

Table 2.6: One-Sample Sign Test Results for the Median of the Perceived Penalty Rates (with weighted and unweighted data)

Alternative Hypothesis	Sampling weights on?	Below	Equal	Above	P-value	Median
Ha: median P < 75%	Yes	796	1	197	< 0.0001	20%
	No	874	2	127	< 0.0001	15%
Ha: median P < 40%	Yes	712	14	268	< 0.0001	20%
	No	793	15	195	< 0.0001	15%
Ha: median P < 20%	Yes	433	159	401	0.14153	20%
	No	511	129	363	< 0.0001	15%

As evident from the presented data, there is extremely large variation in individual perceptions of the penalties. One potential source of such high variability could be the fact that there are

[35] Sampling weights represent "frequency" of a sampling unit in the target population. In other words, the weights show how many people in the target population each selected respondent "represents". Using this information and sampling weights, one can estimate the number of people who have a given variable below, equal to or above a certain threshold. To illustrate this, let's consider the perceived penalty rate variable, P. Let's say our threshold is P = 20%. To find the number of people who have P below 20%, we can simply add the weights for the respondents who have P below that threshold, and then round the sum to the closest integer. This sum is 433.37 in the Tax Evasion Survey data. Consequently, the estimated number of people who perceive the penalty rate to be below 20% is 433. Using the same technique, we can get 159 people who have P equal to 20%, and 401 people who have P greater than 20%. Once we have the numbers of people below and above the threshold, we can calculate the p-value for the one-sample sign test.

[36] Similar results were obtained from one-sample t-tests conducted with the log-transformed data. The t-statistics for 75%, 40% and 20% penalty rates were -11.40, -5.48 and 1.05, respectively. These statistics suggest that the average of the transformed perceived penalty rates is significantly lower than the ln(75%) and ln(40%). However, this is not true about 20% penalty rate. In other words, there is enough evidence suggesting that the geometric mean of the perceived penalty rates is lower than 75% and 40%, but not enough evidence to claim that it is different from 20%. Thus, the results of the parametric tests with the transformed data generally agrees with those of the non-parametric tests.

[37] Nevertheless, the p-value is practically zero when the same test conducted with the unweighted data.

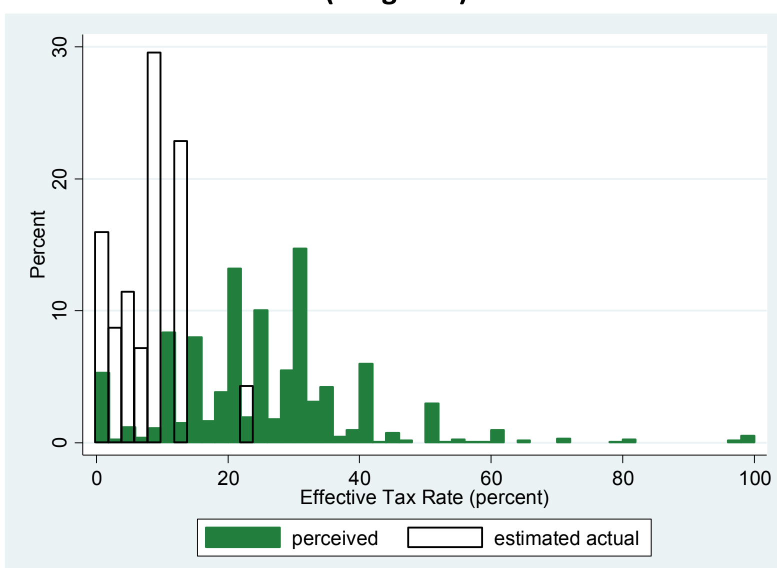
[38] Similar results were obtained when the sample was restricted to people who prepare their tax returns themselves.

several penalty types and rates applicable to tax underpayments. This multiplicity is likely to be reflected in the perceptions too. People may also extrapolate the penalty rates from their knowledge of penalties applied in various other areas of their life (e.g., credit cards, bank overdrafts, overdue utility payments, illegal copying or downloading movies, etc.). Given the variety of individual experiences, such extrapolations are likely to form diverse perceptions of the penalties applied to tax underpayments.

The Tax Rates

It seems that, overall, the US population is also not very knowledgeable about their effective federal income tax rates. Only an estimated 14% of the population would perceive their effective tax rate to be within 5 percentage points from their actual tax rate. Furthermore, the people seem to mostly overestimate their tax rates. While the median of the estimated actual effective tax rate is 8.1%[39], the median perceived effective tax rate is 25%. This overestimation can also be clearly observed in **Figure 2.3** below. **Figure 2.3** demonstrates that there is a substantial number of people whose perceived effective tax rate is even higher than the highest marginal tax rate, which was 39.6% (IRS, 2017b) during the time when the Tax Evasion Survey was administered.[40]

Figure 2.3: Distribution of Perceived and Estimated Actual Effective Federal Income Tax Rates (weighted)



[39] This number is estimated based on the income reported by the ALP Tax Evasion Survey respondents. The actual population median may be even lower. According to Table 1.1 in Publication 1304 (IRS, 2017c), the median income groups is $30-$40 thousand dollars. The effective tax rate for this group is estimated to be 4.8%.

[40] The perceived effective tax rates are also higher than the estimated marginal tax rates by around 9 percentage points, on average.

The magnitude of the overestimation is considerable. The estimated average difference between the perceived and the actual rates is over 18 percentage points with the 95% confidence interval being between 16.3 and 19.9 percentage points. This difference is statistically significant even at the lowest conventional level of significance of 1%. While being smaller, the overestimation is still sizable even for those who prepare their tax returns themselves (see **Table 2.7**).

Table 2.7: Estimated Magnitude of the Misperception for the Effective Federal Income Tax Rate (t-test for the mean difference)

Sample	**Median Difference (Perceived – Actual)**	**Average Difference (Perceived - Actual)**	**Standard Error**	**t-statistic**	**p-value**	**95% CI for the Mean**
All (n = 907)	16.9 (in percentage points)	18.09 (in percentage points)	0.897	20.16	<0.001	[16.33; 19.85]
Only those who prepare their tax returns themselves (n = 364)	15.5 (in percentage points)	15.6 (in percentage points)	1.042	14.95	<0.001	[13.52; 17.62]

There are several plausible explanations why people overestimate their effective tax rate. One of them is that they may confuse effective tax rate with marginal tax rate. To test this hypothesis, marginal tax rates were estimated for the survey respondents, and then correlated with the perceived tax rates. If the hypothesis is true, one would expect the marginal and the perceived rates to be positively correlated. Yet, there is no significant evidence supporting this hypothesis (see **Table 2.8**). The Pearson's correlation coefficients estimated for the relationship between perceived and marginal rates are, in fact, negative, although their magnitudes are small and not always statistically significant. While Spearman's and Kendall's rank correlation coefficients are positive and statistically significant, they are very small and suggest, at best, a weak monotonic association between perceived and marginal tax rates.

Table 2.8: Correlation Coefficients between the Perceived Effective Tax Rates and the Estimated Actual Effective and Marginal Tax Rates

Estimated Actual Tax Rates	**Pearson's Correlation Coefficients**		**Spearman's Correlation Coefficients**	**Kendall's Correlation**	
	with sampling weights	**no sampling weights**		**tau a**	**tau b**
Effective	-0.0525 (0.3430)	0.0487 (0.1426)	0.1323* (0.0001)	0.0948* (< 0.0001)	0.1046* (<0.0001)
Marginal	-0.1295** (0.0383)	-0.016 (0.6303)	0.1059* (0.0014)	0.0732* (0.0006)	0.0868* (0.0006)

NOTES: 1) Spearman's and Kendall's Correlation coefficients have been calculated based on the unweighted data.
2) p-values are in parenthesis.
3) * - statistically significant at 1% level of significance; ** - statistically significant at 5% level of significance.

Alternatively, the overestimation of the tax rates can be explained by the phenomenon known as "over-claiming" – when individuals tend to overestimate their relative contribution to their collective work. Over-claiming has been observed in several studies and in various contexts like married couples sharing household chores (Kruger & Savitsky, 2009; Ross & Sicoly, 1979), academics collaborating on research projects (Caruso, Epley, & Bazerman, 2006), and students working on joint assignments (Savitsky, Van Boven, Epley, & Wight, 2005; Schroeder, Caruso, & Epley, 2016). In all these studies, the participants were asked to estimate the share that they personally contributed to their group's work. The sum of these shares routinely exceeded the logically possible limit of 100%. These findings suggest that people often believe that their contribution is greater than what it really is. Similarly, taxpayers may think that they pay greater proportion of their income as taxes than they actually do.

It is also possible that while responding to the survey question about the perceived tax rates, some respondents conflated federal taxes with state and other taxes. If they did, then this would logically increase the perceived federal tax rates, and thus, at least, partially explain the overestimation. This conflation may still happen despite the fact that the questionnaire explicitly stated that the question was about *federal* taxes. It is likely to occur if a respondent has one mental account[41] for all taxes and/or focuses mostly on how much net income she earns rather than on how much taxes she pays. Such mental accounting can make it difficult to differentiate between federal and the other taxes.

Loss aversion could be another potential explanation to the overestimation of the tax rates. If taxes are viewed as losses, then to the respondents they may loom larger than what they really are. This and the other plausible explanations discussed above are not necessarily mutually exclusive. A combination of the abovementioned biases can be at play producing misperceptions about the tax rates.

[41] Mental accounting is a term coined by Richard R. Thaler (1985). He defines it as "the set of cognitive operations used by individuals and households to organize, evaluate, and keep track of financial activities"(R. H. Thaler, 1999). The concept refers to the tendency of people to categorize their income and expenses by attaching certain mental labels to them like "money allocated for rent", "lunch money", "money from selling my old car", and "money I paid as taxes". These labels serve as mental accounts.

Covariates of the Misperceptions: Regression Analysis Results and Interpretations

How are the misperceptions discussed in the previous section related to taxpayers' individual characteristics? Are there certain groups of taxpayers who are more susceptible to these misperceptions? To answer these questions a series of regression analyses was conducted. In these regression models, the dependent variables are the perceptions of the audit, penalty and tax rates. The independent variables are a set of variables describing personal and social network characteristics, personal experiences, attitudes and beliefs. The list of these covariates and their brief description are shown in **Table 2.9**. The variables for *personal characteristics* include age, race, ethnicity, gender, marital status, education, employment status (i.e., self-employed or not), and estimated marginal and effective tax rates that the respondents pay. The marginal and effective tax rates also serve as proxy variables for income since both were estimated based on the income data. The *social network variables* are proportion of alters who are believed to be audited, proportion of alters with whom the respondent has talked or consulted about taxes in the past 5 years, and proportion of alters who are self-employed. There are also three *personal experience* variables, which are about respondents' experiences with the tax system. These three variables are binary variables and indicate: 1) whether the respondents ever filed a tax return; 2) if the respondent or their spouses have ever been audited; and 3) if the respondent typically prepares their tax returns themselves or have someone else to prepare the returns for them. Another set of independent variables depict some of the respondents' *attitudes, beliefs and views* concerning taxes, certain free-riding issues, public goods and services. For more details regarding these variables, please see the survey questionnaire in **Appendix A**.

Table 2.9: Covariates of the Perceptions and Their Brief Description

Covariates	Description
Personal Characteristics	
Age	in years
Black-African American	= 1 if Black-African American; 0 otherwise
Native American	= 1 if Native American; 0 otherwise
Asian	= 1 if Asian; 0 otherwise
Other Race	= 1 if Other race; 0 otherwise
hispaniclatino	= 1 if Hispanic/Latino; 0 otherwise
male	= 1 if male; 0 otherwise
married	= 1 if married; 0 otherwise
education	= 1 if has Bachelor's degree and above; 0 otherwise
foreignborn	= 1 if foreign born; 0 otherwise
MTR	Marginal federal income tax rate estimated based on the survey questions on family income. Measured in fractions, i.e., range ∈ [0;1].
Estimated Tax Rate	Effective federal income tax rate estimated based on the survey questions on family income. Measured in fractions, i.e., range ∈ [0;1].
selfemployed	= 1 if self-employed; 0 otherwise

Social Network Characteristics	
prop_altersaudited	Proportion of alters who are believed to be audited
prop_alters_talkTaxes	Proportion of alters with whom the respondent has talked or consulted with about taxes in the past 5 years
prop_alterselfemployed	Proportion of alters who are self-employed
Experiences	
hheveraudited	= 1 if self or spouse has ever been audited; 0 otherwise
haventfiledtaxes	= 1 if ever filed taxes or had someone else to file taxes for them; 0 otherwise
preptaxesself	= 1 if prepares taxes himself/herself; 0 otherwise
Attitudes, beliefs, and views	
pcaught	Respondents' subjective probability of being caught if a taxpayer underreports taxes
prob_deduction	Respondents' subjective probability of them claiming a questionable tax deduction
actor_more	= 1 more likely or somewhat more likely to fully report taxes if a famous actor is known to evade taxes; 0 otherwise.
freeriding_never	Total number of "Never ok" responses to 5 separate questions about engaging in 5 different free-riding activities. Maximum is 5 (it is never ok to engage in all these free-riding activities); minimum is 0 (the respondent thinks that it is always ok or sometimes ok to engage in all these 5 free-riding activities). These free-riding activities are: 1. Regularly listen to public radio without ever contributing; 2. Illegally copying, downloading, or streaming movies; 3. Have a dog but not getting it spayed or neutered; 4. Avoid getting the flu vaccine; 5. Avoid paying all of the income tax that you owe.
freeriding_percentage	Average score for 5 questions about percentage of people like respondents who engage in 5 different free-riding activities. These free-riding activities are the same as described in the entry for ***freeriding_never***.
worthpayingtaxes	= 1 if thinks that public goods and services worth paying taxes for; 0 otherwise
importancetaxbenefits	Relative importance of *benefits and public service supported by taxes* when the respondent thinks about taxes and paying his/her taxes. Maximum is 100 points; more points more important.
importancemoraloblig	Relative importance of *a moral obligation to correctly report and pay taxes* when the respondent thinks about taxes and paying his/her taxes. Maximum is 100 points; more points more important.

The main purpose for these analyses is not to develop prediction models, but to see how these covariates are associated with the perceptions of the audit, penalty and tax rates. Rather than predicting the perceptions, these analyses are looking for any statistically significant relationships and the direction of these relationships. For this reason, several alternative model specifications will be examined for each of the dependent variables.

Regression Models for the Perceived Audit Rates

Several regression models for the perceived audit rates were run. The results for some of them are presented in **Table 2.10**. The simplest among those is the linear model. The main advantage of this model is that it is relatively easy to interpret the regression coefficients. However, the model yields outcomes beyond the [0;1] interval for some values of the independent variables. These are unrealistic outcomes since the dependent variable is a proportion, and cannot be negative or greater than one. This issue is typically addressed by using fractional outcome regression (Baum, 2008; Liu, Liu, Hammitt, & Chou, 1999; Papke & Wooldridge, 1996, 2008; Wagner, 2001). Hence, besides the linear model, some *fractional outcome models* were also utilized to model the perceived audit rates. These models are generalized linear models (GLM) with binomial distribution as the family distribution (i.e., the distribution of the dependent variable). In these models, four different link functions were used: logit, probit, log-log and complementary log-log function. Since these link functions generated similar results, only the model with logit as the link function is shown in **Table 2.10**.

Given that the perceived audit rates take non-negative values and that their distribution is right-skewed, gamma distribution was also considered as a family distribution in some GLMs. These models had log-log and complementary log-log functions as the link functions. These are the last two models in **Table 2.10**.

All these different models produced results that are generally consistent with each other. The covariates that are statistically significant in one model are usually also significant in the others. Their coefficient signs are mostly the same across the models too.

Table 2.10: Selected Regression Models with the Perceived Audit Rates as a Dependent Variable (n = 890)

Independent Variables	Correlation Coefficients	Linear Model		GLM, family - binomial, link - logit		GLMs, family- gamma, link functions:			
						log-log		clog-log	
		Coeff.	p-values	Coeff.	p-values	Coeff.	p-values	Coeff.	p-values
Personal Characteristic:									
Age	-0.1100	-0.00092	0.145	-0.00464	0.170	0.00286	0.179	-0.00021	0.962
Black-African American	0.0809	0.02283	0.486	0.18047	0.239	0.23180	0.009	0.21838	0.242
Native American	0.0293	-0.01985	0.775	-0.08009	0.815	-0.11835	0.451	-0.16136	0.512
Asian	0.0503	0.12440	0.183	0.88570	0.057	0.64438	0.016	1.03674	0.035
Other Race	0.1445	-0.02501	0.546	-0.12566	0.525	0.04538	0.681	-0.05982	0.744
hispaniclatino	0.2646	0.07416	0.024	0.43660	0.007	0.33905	0.001	0.46328	0.013
male	-0.3603	-0.09519	0.000	-0.58801	0.000	-0.20751	<0.001	-0.47031	<0.001
married	-0.0973	-0.00664	0.719	-0.01643	0.874	0.10513	0.045	0.04704	0.752
education	-0.3320	-0.07737	<0.001	-0.52904	<0.001	-0.11706	0.064	-0.40577	0.000
foreignborn	0.0171	-0.03595	0.221	-0.26991	0.112	-0.43096	<0.001	-0.49593	0.116
MTR	-0.3825	-0.33539	0.007	-1.87902	0.003	-1.58799	<0.001	-2.03112	0.005
selfemployed	-0.1405	-0.04865	0.007	-0.37988	0.003	-0.05793	0.369	-0.26629	0.055
Social Network Characteristics:									
prop_altersaudited	0.1474	0.23201	0.010	1.18110	0.008	0.55214	0.115	1.02766	0.042
prop_alters_talkTaxes	-0.0115	0.00984	0.747	0.08640	0.631	0.20698	0.071	0.17616	0.458
prop_alterselfemployed	-0.0501	-0.05993	0.131	-0.36649	0.116	-0.15491	0.274	-0.30180	0.163
Experiences:									
hheveraudited	-0.0231	0.00485	0.788	-0.04948	0.678	-0.11848	0.050	-0.10186	0.634
haventfiledtaxes	0.1909	0.03274	0.420	0.05802	0.747	0.13671	0.119	0.05142	0.716
preptaxesself	-0.2670	-0.06200	0.001	-0.37973	<0.001	-0.18522	0.001	-0.35925	<0.001
Attitudes, beliefs, and views:									
prob_deduction	0.1580	0.07327	0.007	0.44688	0.004	0.38594	0.001	0.55634	0.009
actor_more	0.2690	0.02904	0.319	0.15821	0.284	0.24449	0.003	0.26395	0.022

freeriding_never	0.0370	0.00133	0.876	0.01069	0.819	0.02092	0.394	0.02944	0.484
freeriding_percentage	-0.1453	-0.00041	0.431	-0.00242	0.376	-0.00420	0.007	-0.00445	0.135
worthpayingtaxes	-0.1579	-0.02207	0.209	-0.11542	0.253	-0.14277	0.014	-0.14216	0.214
importancetaxbenefits	0.0281	0.00004	0.939	0.00004	0.987	0.00237	0.130	0.00049	0.862
importancemoraloblig	0.1049	0.00057	0.220	0.00348	0.176	0.00274	0.010	0.00352	0.135
_cons	--	0.41529	<0.001	-0.26717	0.401	-0.21193	0.135	-0.76744	0.010
AIC	--		-859.4		721.3		-1041.0		-983.8
BIC	--		-734.8		845.9		-916.4		-859.3

Among those describing personal characteristics, statistically significant independent variables were *hispaniclatino*, *male*, *education*, *selfemployed* and *MTR*. According to the results, Hispanics/Latinos had, on average, higher audit rate perceptions than the others. Males, on the other hand, had lower perceptions than females. This is consistent with the findings from some other studies showing that females typically have higher risk perceptions than males (Barke, Jenkins-Smith, & Slovic, 1997; Brody, Zahran, Vedlitz, & Grover, 2008; Finucane, Slovic, Mertz, Flynn, & Satterfield, 2000; Flynn, Slovic, & Mertz, 1994; van der Linden, 2015). The coefficient for *education* variable was also negative. Given that the great majority of people overestimate the audit rate, this can be interpreted as more educated individuals (individuals with university degrees, to be exact) being more accurate in their perceptions of the audit rate than the rest. Similarly, self-employed individuals, on average, were more accurate in their perceptions than the rest as the coefficient for *selfemployed* was negative too. Higher rates of marginal tax were associated with lower perceptions of the audit rate. This translates into a negative correlation between family income and perceived audit rates since marginal tax rates and income are positively correlated. The other personal-characteristic variables, namely age, race, marital status, and place of birth variables, had mostly statistically insignificant coefficients.

As expected, the proportion of alters who are believed to be audited (*prop_altersaudited*) was positively associated with the perceived audit rates. Moreover, this variable had statistically significant coefficients in most of the considered models. However, there was not enough evidence for statistically significant relationship between the other two social-network variables (*prop_alters_talkTaxes* and *prop_alterselfemployed*) and the perceptions of the audit rate.

Surprisingly, having personal audit experience did not seem to affect the perceptions in a statistically significant way. While those who have been audited or whose spouse has been audited generally had slightly lower perceptions than the others, the coefficients for *hheveraudited* were not significant. The exception was the coefficient in the GLM with gamma distribution as the family distribution and log-log as the link function. In this model, all three personal experience variables (*hheveraudited*, *haventfiledtaxes* and *preptaxesself*) were statistically significant. The coefficient for *haventfiledtaxes* was positive in all models. This suggests that people who have never filed taxes or had somebody else to file taxes for them may have higher perceptions of the audit rates than the others. This difference, however, was statistically significant in only one model. Unlike these people, individuals who prepared their tax returns themselves, on average, perceived the audit rates to be lower than what the others did. The coefficients for *preptaxesself* were significant in all models even at the 1% level of significance.

The independent variables describing *attitudes, beliefs and views* mostly had insignificant coefficients. Only one variable in this group had significant coefficients across all models. This was *prob_deduction*, which is respondents' subjective probability of them claiming a questionable tax deduction. This variable had significant coefficients even at the 1% level of significance. The coefficients were positive, suggesting that individuals who are more prone to claim a questionable deduction are likely to perceive the audit rates to be higher than what they really are.

Thus, these regression analyses generate a profile of individuals who are more disposed to overestimate the audit rates. These people are female, Hispanic/Latino, with education below bachelor's degree, low income, not self-employed, with higher proportion of alters who are believed or known to be audited, have not filed taxes at all or have somebody else to file taxes for them and are more inclined to claim a questionable deduction. In contrast to this profile, highly educated, high-income males who are self-employed and prepare their tax returns themselves typically have lower perceptions of the audit rate than the rest.

Regression Models for the Perceived Penalty Rates

Three types of regression models were considered for the perceived penalty rates. All three models are shown in **Table 2.11**. The first and the simplest one was again the linear model. However, the range and distribution of the perceived penalty rates[42] suggested that log-linear model might be a better fit. The log-linear functional form was also confirmed by the Box-Cox test results.[43] Furthermore, this model had lower AIC and BIC values than the linear model. A problem with the log-linear model is the loss of some observations during the logarithmic transformation of the perceived penalty rates. This happens because several respondents perceived the penalties to be exactly 0. To address this problem, a GLM was estimated. This GLM had gamma distribution as the family distribution[44] and log as a link function. It should be noted that the GLM is probably the "best" fit among the models since it had the lowest AIC and BIC value.

[42] The perceived penalty rates took only non-negative values, had only few zeros and their distribution was severely skewed to the right.

[43] The estimated theta (lambda) was very close to zero (-0.006609, to be exact) and the p-value for it was 0.706. Therefore, there was not enough evidence to say that theta was different from zero, which indicates log-linear functional form.

[44] The GLM family test (modified Park Test) yielded a coefficient close to 2 (1.92 with SE = 0.35, to be exact). This suggested that gamma distribution might be the appropriate family distribution.

Table 2.11: Selected Regression Models with the Perceived Penalty Rates as a Dependent Variable

Independent Variables	Correlation Coefficients	Linear Model		Log-Linear Model		GLM, family - gamma, link - log	
		Coefficients	p-values	Coefficients	p-values	Coefficients	p-values
Personal Characteristic:							
Age	-0.2237	-0.00203	0.766	-0.00954	0.069	-0.00362	0.601
Black-African American	0.3959	2.13026	0.104	0.33759	0.387	0.55338	0.149
Native American	-0.0071	0.34587	0.289	-0.06889	0.882	-0.04601	0.929
Asian	-0.0366	-2.05161	0.027	-0.90547	0.057	-1.24899	0.006
Other Race	-0.0448	-0.45750	0.178	-0.51150	0.112	-0.27821	0.275
hispaniclatino	-0.0756	-0.32519	0.166	-0.07993	0.703	-0.23880	0.261
male	0.1360	0.60072	0.060	0.22680	0.160	0.21453	0.208
married	-0.2069	0.05032	0.812	0.07255	0.637	-0.01451	0.932
education	-0.1032	-0.33893	0.155	-0.04025	0.798	-0.00165	0.992
foreignborn	0.3108	2.45665	0.038	0.86192	0.024	1.01755	0.004
MTR	-0.1399	-1.67382	0.245	-0.42310	0.709	-1.76498	0.168
selfemployed	-0.0519	-0.12799	0.532	-0.23182	0.265	-0.38112	0.128
Social Network Characteristics:							
prop_altersaudited	-0.0392	-0.13695	0.880	1.20028	0.122	0.64255	0.446
prop_alters_talkTaxes	-0.0496	0.23459	0.591	-0.08606	0.792	0.63922	0.147
prop_alterselfemployed	0.0006	-0.23203	0.584	-0.04685	0.887	-0.48046	0.204
Experiences:							
hheveraudited	-0.0945	-0.72083	0.039	-0.32922	0.081	-0.58431	0.002
haventfiledtaxes	0.0316	0.65635	0.065	0.87082	0.009	0.66030	0.042
preptaxesself	0.1208	0.42268	0.184	0.08444	0.579	-0.03425	0.848
Attitudes, beliefs, and views:							
pcaught	0.2942	1.84077	0.035	1.41598	<0.001	0.99226	0.005
prob_deduction	-0.0758	-0.64510	0.131	0.00960	0.969	-0.07048	0.779
actor_more	-0.0378	-0.84034	0.122	-0.14487	0.494	-0.05629	0.771
freeriding_never	-0.1747	-0.18895	0.059	-0.00988	0.895	-0.10056	0.203
freeriding_percentage	-0.0737	0.00126	0.785	0.00182	0.637	0.00027	0.951
worthpayingtaxes	-0.1405	-0.06139	0.696	-0.04813	0.733	0.12944	0.457
importancetaxbenefits	0.1753	0.01575	0.099	0.00570	0.166	0.00766	0.171
importancemoraloblig	-0.0063	0.00684	0.144	0.00325	0.291	0.00520	0.140
_cons	--	0.32570	0.665	-1.71359	0.004	-0.81711	0.223
		n = 887		n = 880		n = 887	
AIC	--		3489.2		2847.2		489.3
BIC	--		3618.5		2976.3		618.6

Across all these three models, only five independent variables had statistically significant coefficients. These were: *Asian*, *foreignborn*, *hheveraudited*, *haventfiledtaxes* and *pcaught*. The coefficient for *Asian* was negative, suggesting that those of Asian race generally had lower perceptions of the penalty rates than the Whites (which was the reference group). Unlike *Asian*, the coefficient for *foreignborn* was positive. This indicated that those born outside of the US had, on average, higher perceptions of the penalty than the rest. Those who have never filed taxes also had higher perceptions than the others. Being audited or having a spouse who have been audited, on the other hand, was negatively associated with the perceived penalties. *hheveraudited* variable had negative and statistically significant coefficients in the models. This suggests that the actual penalties are generally lower than what the taxpayers believe them to be prior to being audited.

Interestingly, *pcaught* was positively correlated with the perceived penalty rates. The perceived penalty rates were usually higher for those who thought that the probability of being caught were high. Similar relationships were observed in some other empirical studies of risks and benefits. These studies found that when people perceived that the risks of a certain activity is high, then they tend to assess the benefits from that activity as low, and vice-versa (Finucane et al., 2000; Fischhoff, Slovic, Lichtenstein, Read, & Combs, 1978).

While providing information about the associations between the perceptions and the covariates, the models in **Table 2.11** do not tell us who are more likely to estimate the penalty rates reasonably well. For that purpose, additional logit and multinomial logit regression models were run. The logit model and the average marginal effects estimated based on it are presented in **Table 2.12**. In this model, the dependent variable was a binary variable which took values 1 if a respondent's perceived penalty rate was within 5 percentage points from the typical penalty rate of 20%[45]; and 0 if otherwise. The independent variables were the same as in the previous models. However, the variables with statistically significant coefficients were not quite the same. This time the coefficients were significant for *Native American*, *foreignborn*, *preptaxesself*, *freeriding_never*, and *worthpayingtaxes*. Native Americans were less likely to be accurate about the penalty rate than the Whites.[46] People born outside of the US were also less likely to have reasonably accurate perceptions about the penalties. They, on average, were 17 percentage points less likely to predict the penalty rate to be around 20% than the others (see "dy/dx" column in **Table 2.12**). The coefficient for *worthpayingtaxes* was negative too, but was significant only at 10% level of significance. Unsurprisingly, people who prepared their tax returns themselves had slightly better chances of estimating the rate correctly than the rest. The estimated average marginal effect for *preptaxesself* was positive 0.086, although it was

[45] Little over 26% of the respondents had perceived penalty rate within 5 percentage points from the penalty rate of 20%. While this margin of 5 percentage points may seem large, narrower margins did not produce any substantially different results.

[46] The results about Native Americans should be taken with a large grain of salt. There was a very small number of Native-Americans (only 13) in the sample used in the analysis.

only significant at 10% level of significance. Disapproval of the free-riding activities was also positively correlated with the probability of the reasonable prediction. People who disapproved more free-riding activities were more likely to predict the penalties reasonably well. Each disapproved activity was associated with an average increase of 0.042 in the probability of the reasonable prediction.

Table 2.12: Logit Model for the Penalty Rate Being Estimated Reasonably Well (i.e., within 5 percentage points), n = 887.

Independent Variables	Logit Model			Average Marginal Effects (dPr./dx)
	Coefficients	Linearized S.E.	p-values	
Personal Characteristic:				
Age	-0.01887	0.0124	0.128	-0.00317
Black-African American	-0.26474	0.5556	0.634	-0.04228
Native American	-2.55969	1.1795	0.030	-0.21920
Asian	0.62791	0.7811	0.422	0.11722
Other Race	-0.69029	0.6419	0.282	-0.10127
hispaniclatino	0.19896	0.4573	0.664	0.03425
male	-0.16880	0.2737	0.538	-0.02830
married	-0.11401	0.2895	0.694	-0.01932
education	0.26175	0.2738	0.339	0.04466
foreignborn	-1.25955	0.4716	0.008	-0.17024
MTR	-1.63341	1.8932	0.388	-0.27432
selfemployed	-0.50291	0.3594	0.162	-0.07613
Social Network Characteristics:				
prop_altersaudited	0.14040	1.3527	0.917	0.02358
prop_alters_talkTaxes	0.04401	0.4590	0.924	0.00739
prop_alterselfemployed	1.02327	0.6515	0.117	0.17185
Experiences:				
hheveraudited	0.40757	0.3198	0.203	0.07232
haventfiledtaxes	-0.22021	0.8001	0.783	-0.03539
preptaxesself	0.50605	0.2895	0.081	0.08572
Attitudes, beliefs, and views:				
pcaught	-1.02700	0.7928	0.196	-0.17248
prob_deduction	0.40805	0.4003	0.308	0.06853
actor_more	0.27731	0.3473	0.425	0.04783
freeriding_never	0.24800	0.1261	0.050	0.04165
freeriding_percentage	-0.00678	0.0079	0.388	-0.00114
worthpayingtaxes	-0.50071	0.2733	0.067	-0.08497
importancetaxbenefits	0.01236	0.0076	0.103	0.00208
importancemoraloblig	0.00915	0.0062	0.141	0.00154
_cons	-0.63659	0.9951	0.523	--

NOTES: 1) The base outcome is that a respondent either under- or over-estimated the penalty rate by more than 5 percentage points. 2) dPr./dx is the average change in the probability of predicting the penalty reasonably well per unit change in variable x. 3) dPr./dx for the dummy variables is the discrete change from the base level.

These results provide some idea about individuals who might be better at estimating the penalty rate correctly. These people are non-Native American, US-born taxpayers who prepare their tax returns themselves and who mostly disapprove free-riding activities.

For a more detailed analysis of people who wrongly estimated the penalties, a multinomial logit model was used. This model allows to detect if the respondent characteristics are associated with underestimating and then separately with overestimating the penalty rate. In this case, the dependent variable, unlike in the logit model, has three different outcomes: 1) "underestimated" (460 respondents); 2) "estimated reasonably well" (268 respondents); and 3) "overestimated" the penalty rate (275 respondents). The second outcome – "estimated the penalty rate reasonably well" – was selected as the base (or reference) outcome. Consequently, the estimated multinomial logit equations had the following form:

$$\ln\left(\frac{P(understimated)}{P(estimated\ reasonably\ well)}\right) = b_{10} + b_{12}X_2 + b_{13}X_3 + \cdots + b_{1k}X_k \qquad (2.1)$$

$$\ln\left(\frac{P(overstimated)}{P(estimated\ reasonably\ well)}\right) = b_{20} + b_{22}X_2 + b_{23}X_3 + \cdots + b_{2k}X_k \qquad (2.2)$$

where $P(understimated)$ is the probability that the individual underestimated the penalty rate; $P(overstimated)$ is the probability that the individual overestimated the penalty rate; $P(estimated\ reasonably\ well)$ is the probability that the individual estimated the penalty rate reasonably well; $\boldsymbol{X}$-s are the independent variables; and $\boldsymbol{b}$-s are the regression coefficients. These regression coefficients, their standard errors and p-values can be found in **Table 2.13**. This table also provides relative risk ratios[47] (RRR) for each independent variable. The last four columns in the table show estimates for equation (2.2), and the previous four columns are the estimates for equation (2.1).

[47] Relative risk ratios (RRR) are obtained by exponentiating the multinomial regression coefficients. They generally show by how many times $P(k^{th}\ outcome)/P(base\ outcome)$ ratio changes per unit change in the independent variable. For instance, RRR for age variable is 1.023 for the "underestimated the penalty rate" outcome (see **Table 2.13**). This means that a one-year increase in age will be associated with an increase in $P(underestimated)/P(estimated\ reasonably\ well)$ ratio by a factor of 1.023. Alternatively, the ratio of the probabilities is expected to go up by 2.3% [= (1.023 - 1) *100%] for a unit increase in age. This interpretation can become obvious by exponentiating equation (2.1) and by making some minor algebraic manipulations.

Table 2.13: Multinomial Logit Model for the Perceived Penalty Rates, n = 887

Independent Variables	"Underestimated the penalty rate"				"Overestimated the penalty rate"			
	Coefficient	Relative Risk Ratio	S.E. of the Coefficient	p-values	Coefficient	Relative Risk Ratio	S.E. of the Coefficient	p-values
Personal Characteristic:								
Age	0.02252	1.023	0.0131	0.086	0.01378	1.014	0.0133	0.301
Black-African American	0.00963	1.010	0.6049	0.987	0.39258	1.481	0.6154	0.524
Native American	2.96608	19.416	1.3316	0.026	2.25891	9.573	1.2400	0.069
Asian	-0.25098	0.778	0.8637	0.771	-0.79820	0.450	0.9397	0.396
Other Race	1.06951	2.914	0.7189	0.137	0.35990	1.433	0.6876	0.601
hispaniclatino	-0.44775	0.639	0.4820	0.353	0.07447	1.077	0.5188	0.886
male	0.06117	1.063	0.2934	0.835	0.32591	1.385	0.3330	0.328
married	-0.02727	0.973	0.3157	0.931	0.30021	1.350	0.3358	0.371
education	-0.17712	0.838	0.3176	0.577	-0.40770	0.665	0.3195	0.202
foreignborn	1.04478	2.843	0.5260	0.047	1.40145	4.061	0.5158	0.007
MTR	1.42314	4.150	2.1030	0.499	1.81637	6.149	2.2701	0.424
selfemployed	0.65929	1.933	0.3936	0.094	0.14004	1.150	0.4685	0.765
Social Network Characteristics:								
prop_altersaudited	-1.14473	0.318	1.5502	0.460	0.82212	2.275	1.5959	0.607
prop_alters_talkTaxes	0.09254	1.097	0.4874	0.849	-0.18931	0.828	0.5698	0.74
prop_alterselfemployed	-1.18436	0.306	0.6991	0.091	-0.91995	0.399	0.7559	0.224
Experiences:								
hheveraudited	-0.22865	0.796	0.3432	0.505	-0.66663	0.513	0.4097	0.104
haventfiledtaxes	-0.73463	0.480	0.8659	0.396	0.68677	1.987	0.8861	0.439
preptaxesself	-0.46614	0.627	0.3110	0.134	-0.57089	0.565	0.3427	0.096
Attitudes, beliefs, and views:								
pcaught	0.07607	1.079	0.8637	0.930	1.70268	5.489	0.8435	0.044
prob_deduction	-0.39459	0.674	0.4640	0.395	-0.42185	0.656	0.4745	0.374
actor_more	-0.61276	0.542	0.3700	0.098	0.04296	1.044	0.3871	0.912
freeriding_never	-0.20867	0.812	0.1402	0.137	-0.28524	0.752	0.1439	0.048
freeriding_percentage	0.00952	1.010	0.0088	0.281	0.00415	1.004	0.0087	0.632
worthpayingtaxes	0.62128	1.861	0.3020	0.040	0.33569	1.399	0.3196	0.294
importancetaxbenefits	-0.01498	0.985	0.0079	0.059	-0.00899	0.991	0.0087	0.300
importancemoraloblig	-0.01177	0.988	0.0068	0.082	-0.00573	0.994	0.0071	0.423
constant	0.09409	1.099	0.9993	0.925	-0.24998	0.779	1.1706	0.831

NOTE: 1) The base outcome is "predicted the penalty rate reasonably well (i.e., within 5 percentage points); 2) Constant of the relative risk ratios estimates baseline relative risk for each outcome.

As evident from **Table 2.13**, there were several independent variables that have positive and statistically significant coefficients in equation (2.1). These were *Age*, *Native American*, *foreignborn*, *selfemployed*, and *worthpayingtaxes*. Therefore, one may conclude that older, self-employed people born outside of the U.S. were more likely to underestimate the penalty rate than correctly estimate it. Their relative probability of underestimating rather than correctly estimating was also higher if they believe that the public goods and services were worth paying taxes for. Furthermore, this relative probability was expected to be higher by a large factor of 19.42 for Native Americans relative to Whites, if all the other characteristics were the same. To put it differently, Native Americans were more likely than Whites to underestimate the penalty rate rather than estimate it reasonably well.

In the same equation, there were four other variables that had negative and significant coefficients. Yet, they were only significant at 10% level of significance. These were the coefficients for *prop_alterselfemployed*, *actor_more*, *importancetaxbenefits* and *importancemoraloblig*. Remarkably, higher proportions of alters who are self-employed were associated with lower relative probability of underestimating rather than correctly estimating the penalty rate. The relative probability decreased by almost 70% [= (0.306 - 1)*100%] per each percentage point increase in the proportion of alters who are self-employed, other things being constant.

In equation (2.2), two personal characteristics: being Native American and being born outside of the US had again positive and statistically significant coefficients. The RRRs for *Native American* and *foreignborn* were also high by being 9.57 and 4.06, respectively. In other words, the relative probability of overestimating rather than correctly estimating the penalty rate was 857% [= (9.57 – 1)*100%] higher for Native Americans than for Whites with the same characteristics. For individuals born outside of the US, it was 306% higher than the US-born individuals with the same characteristics.

Another variable that had positive and statistically significant coefficient in equation (2.2) was *pcaught* – respondents' subjective probability of being caught if a taxpayer underreports taxes. The magnitude of the coefficient (and RRR) was not trivial. Per each percentage point increase in *pcaught*, $P(overestimated)/P(estimated\ reasonably\ well)$ ratio was expected to go up by a factor of almost 5.5, holding everything else constant. More generally, if individuals believe that the probability of being caught is high, then one would expect them to be more likely to overestimate the penalty rate rather than estimate it correctly. This conclusion is consistent with the findings of the regression analyses discussed earlier.

Equation (2.2) also had statistically significant coefficients that were negative, namely the coefficients for *preptaxesself* and *freeriding_never*. For individuals who prepared their tax returns themselves, the relative probability of overestimating rather than correctly estimating the penalty rate was about 44% [= (0.565 – 1)*100%] lower than the others with otherwise the same characteristics. This relative probability was also lower for people who disapproved more free-riding activities. If a person disapproved one additional free-riding activity, then $P(overestimated)/P(estimated\ reasonably\ well)$ ratio was expected to decrease by about 25% [= (0.752 – 1)*100%].

Regression Models for the Perceived Tax Rates

A linear model was used to examine the relationships between the perceived tax rates and different personal characteristics, experiences, attitudes and beliefs.[48] This model had the perceived tax rates as the dependent variable. The independent variables were the same as in the models for perceived audit and penalty rates. The only exception was the estimated actual effective tax rates, which replaced the estimated marginal tax rates.[49] This replacement helps to tease out the associations between the respondents' individual characteristics and their tax-rate perceptions unrelated to the variations in the actual tax rate, since it is controlled for. This provides an important context for interpreting the other regression coefficients.[50] For example, in the linear model (*Model 1* in **Table 2.14**), the coefficient for *Age* was significant and -0.00142. This means that all other things being the same, including the effective tax rates, if one person was older than another by 10 years, then her perception of the tax rate would be, on average, 1.42 percentage points less than the other's.

Some other statistically significant and negative coefficients in this model were those for *male*, *selfemployed*, and *preptaxesself*. This suggests that self-employed men who prepare their tax returns themselves, generally, had lower perceptions of their tax rates than the rest, all other things, including actual effective tax rate, being equal. Interestingly, these coefficients had about the same magnitude.

Some of the race and ethnicity coefficients were significant, although marginally so sometimes. The coefficient for *Native American* was large by being 0.183 and statistically significant. In other words, holding everything else constant, Native Americans' perceived tax rates were higher than those of Whites by over 18 percentage points, on average. In contrast, those who identified themselves as "Other race", typically had lower perceptions of the tax rates than Whites. There was also a sizable difference in the perceptions between Hispanics/Latinos and the rest. Hispanics and Latinos usually had higher perceived tax rates than the others. The coefficient for *hispaniclatino* was 0.052, though it was significant only at 10% level of significance.

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[48] Since the tax rates are theoretically bounded by 0% and 100%, several types of fractional response models were also estimated. These were mostly GLM-s with binomial family distribution, but with different standard link functions like probit, logit, log-log and clog-log. Nevertheless, the GLM-s did not seem to be any better than the linear model. The linear model produced results similar to those generated by the GLM-s. Coefficients significant in this model usually were also significant in the GLM-s. Moreover, these coefficients were comparable to the average marginal effects estimated based on the fractional response models (compare the coefficients of the linear model with *dy/dx* column in **Table C.1, Appendix C**). Finally, the linear model seemed to be a better fit too since it had the lowest AIC and BIC.

[49] The model was run with the marginal tax rate as an independent variable too. However, the marginal tax rate did not have statistically significant coefficient. This result agrees with the findings of the previous section. There did not seem to be any substantial association between perceived tax rates and estimated marginal tax rates.

[50] Michael Furr (2011) briefly discusses the importance of similarly structured models in his book *Scale Construction and Psychometrics for Social and Personality Psychology* (page 87).

None of the considered social network variables had significant coefficients, and only two of the variables describing attitudes, beliefs and views were correlated with the perceived tax rates. These two variables were *pcaught* and *prob_deduction*. The coefficient for the former (respondents' subjective probability of being caught if a taxpayer underreports taxes) was positive, but it was only significant at 10% level of significance. The coefficient for the latter (respondents' subjective probability of them claiming a questionable tax deduction) was also positive and statistically significant even at 1% level of significance. Thus, both of these subjective probabilities were positively associated with the perceptions of the tax rates.

Table 2.14: Linear Regression Models for the Perceptions of Effective Federal Income Tax Rate (n = 887)

Independent Variables	Dependent Variable:							
	Perceived Effective Tax Rate (*Model 1*)				**|Perceived - Actual|** (*Model 2*)			
	Correlation Coefficients	**Coefficients**	**S.E.**	**p-values**	**Correlation Coefficients**	**Coefficients**	**S.E.**	**p-values**
Personal Characteristic:								
Age	-0.1935	-0.00142	0.0006	0.016	-0.2339	-0.00143	0.0006	0.011
Black-African American	0.0286	-0.00598	0.0379	0.875	0.1001	0.00544	0.0354	0.878
Native American	0.1496	0.18316	0.0749	0.015	0.1531	0.18323	0.0712	0.010
Asian	0.0022	-0.01046	0.0330	0.751	0.0045	0.00625	0.0293	0.831
Other Race	0.0020	-0.06854	0.0358	0.056	0.0374	-0.06830	0.0345	0.048
hispaniclatino	0.1755	0.05228	0.0278	0.060	0.2216	0.05981	0.0261	0.022
male	-0.1695	-0.03767	0.0140	0.007	-0.2047	-0.03956	0.0131	0.003
married	0.0028	0.02125	0.0163	0.191	-0.1316	-0.00378	0.0154	0.806
education	-0.0554	-0.01479	0.0138	0.285	-0.1829	-0.03751	0.0126	0.003
foreignborn	0.0696	0.00961	0.0260	0.712	0.0870	0.00909	0.0244	0.710
Estimated Tax Rate	-0.0547	0.23455	0.1650	0.156	--	--	--	--
selfemployed	-0.0819	-0.03226	0.0156	0.040	-0.1039	-0.02899	0.0131	0.027
Social Network Characteristics:								
prop_altersaudited	-0.0039	-0.11294	0.1308	0.388	0.0198	-0.08879	0.1274	0.486
prop_alters_talkTaxes	0.0289	0.01299	0.0262	0.621	0.0119	0.01648	0.0230	0.473
prop_alterselfemployed	-0.0008	0.00600	0.0341	0.860	0.0031	0.00295	0.0326	0.928
Experiences:								
hheveraudited	0.0444	0.01766	0.0189	0.351	0.0101	0.01317	0.0176	0.454
haventfiledtaxes	0.0926	0.02009	0.0507	0.692	0.1686	0.04526	0.0469	0.335
preptaxesself	-0.1184	-0.04437	0.0165	0.007	-0.1645	-0.04774	0.0156	0.002
Attitudes, beliefs, and views:								
pcaught	0.2290	0.08187	0.0443	0.065	0.3210	0.07891	0.0410	0.055
prob_deduction	0.1812	0.06248	0.0231	0.007	0.2004	0.06855	0.0223	0.002
actor_more	0.1719	0.00714	0.0202	0.724	0.2386	0.00951	0.0191	0.619
freeriding_never	-0.0456	-0.00037	0.0071	0.958	-0.0400	0.00162	0.0069	0.815
freeriding_percentage	-0.0653	-0.00009	0.0005	0.848	-0.1262	-0.00035	0.0005	0.460

worthpayingtaxes	-0.0302	-0.00128	0.0161	0.937	-0.0941	-0.00591	0.0150	0.694
importancetaxbenefits	0.0153	0.00024	0.0004	0.575	0.0761	0.00051	0.0004	0.213
importancemoraloblig	-0.0689	-0.00035	0.0003	0.274	-0.0736	-0.00035	0.0003	0.240
_cons	NA	0.29320	0.0595	0.000	NA	0.26487	0.0571	0.000
R-squared	--	0.1902			--	0.2808		
AIC	--	-1047.4			--	-1144.6		
BIC	--	-918.2			--	-1020.1		

Another linear model was estimated to see who are more likely to misjudge tax rates. The model had the absolute difference between the perceived and actual tax rates as the dependent variable, instead of the perceived tax rates. The estimates of this model are also in **Table 2.14** (*Model 2*). Note that the variables that had significant coefficients in the first model were also significant in this model. Moreover, these coefficients had the same signs and about the same magnitudes. There was one variable, however, that had significant coefficient in the second model, but not in the first one. This was the variable for education. Its coefficient was negative, as expected. The coefficient suggested that people with a university-level education have more accurate perceptions of their tax rates than the others. The gap between the perceived and actual rate is about 3.8 percentage points smaller for these people than for their counterparts with the same characteristics but with lower educational achievements.

To sum up, the results show that older, non-Hispanic/non-Latino, university-educated, self-employed men who prepare their tax returns themselves had usually more accurate perceptions of their tax rates. People who identified themselves as “Other race” were also more accurate than Whites in their perceptions of the tax rates, on average. Unlike them, Native Americans had larger gaps between the perceived and actual rates than Whites.

Discussion and Limitations

Discussion of the Results

The findings of this chapter suggest that the U.S. population is largely uninformed about the key elements of the US tax system like the audit, penalty and tax rates. The chapter has also shown that taxpayers’ perceptions of these key elements exhibit substantial heterogeneity. People mostly overestimate the audit rate, as well as their tax burden, and these overestimations vary considerably. Taxpayers also have misperceptions about the penalty rates. While many people underestimate the penalties, there are some who substantially overestimate them. There are also certain groups of people who are more susceptible to all these misperceptions than others.

These findings have both theoretical and practical implications. To begin with, in the light of these findings, the assumption of the commonly used tax evasion model, the A-S model, that taxpayers are fully informed seems less reasonable. Even if taxpayers calculate their expected utility regarding tax evasion, these calculations are likely to be based on substantially inaccurate values of the probability of detection, penalties and tax rates. Thus, in the A-S model, it might be more realistic to express taxpayers' expected utility functions in terms of their perceived probability of detection, perceived penalty rates and perceived tax burden (as was already argued in Chapter 1). However, then these three elements of the model can no longer be safely assumed to be independent of each other. The analysis in this chapter indicates that people's perceptions of the penalty rate are positively associated with their subjective probabilities of detection. Consequently, both theoretical and empirical models of tax evasion, should, at the very least, consider the relationship between perceived penalty rates and subjective probabilities of detection.

Moreover, if the perceptions matter more than the actual values, then this may provide some behavioral intervention opportunities. For example, since people tend to overestimate the audit rates, then even low relative number of audits may still have large deterrence effects, and tax authorities can and probably do capitalize on that. Tax authorities may improve tax compliance without increasing the frequency of the audits by simply making the audits more salient. The salience can be augmented either by publicizing audits in the mass media or by just reminding taxpayers right before or during a tax season that their tax returns can be examined. Such reminders can be a one- or two-sentence message placed on the top of the tax return forms. As an example, this message can say: "*Tax returns are regularly being audited to make sure that the information provided is accurate. The IRS reserves the right to examine the accuracy of your tax return.*"[51] There is some supporting empirical evidence that increasing the salience of the audits (or the possibility of detection) can improve the compliance, at least, in the short run (Bérgolo, Ceni, Cruces, Giaccobasso, & Perez-Truglia, 2017; Bott, Cappelen, Sørensen, & Tungodden, 2017; Kleven, Knudsen, Kreiner, Pedersen, & Saez, 2011; Meiselman, 2018; Slemrod, Blumenthal, & Christian, 2001).

The salience of the audits (or the possibility of detection) might also be boosted by highlighting the penalties too, since the perceptions of the penalties and subjective probabilities of detection are found to be positively correlated. Besides, the salience of the penalties might itself have a deterrence effect as suggested by the results of a controlled field experiment in Detroit, USA (Meiselman, 2018).

Finally, the overestimation of the tax rates may also have its own policy implications. It may warrant a behavioral intervention too. If such overestimation is positively associated with the non-compliance, then tax authorities may want to debunk this misperception. And if such debunking is required, then it should be considered to focus the efforts on the groups who have been identified in this chapter as the most vulnerable to the misperception. A potential (and

[51] Obviously, the exact wording of the message should be tested to see if it has the intended effects before it is used as a large-scale behavioral intervention.

relatively easy) way of debunking the misperception could be simply including "effective tax rate" line on the return.

Limitations of the Data and the Analyses

There are several data related issues that need to be noted. First, in any survey like the ALP Tax Evasion survey, there is always a chance that some respondents may misinterpret or misunderstand some questions due to various reasons. As was already mentioned, the question about the audit rates might be one of such questions. Specifically, some respondent may not know what a tax audit is. They may misinterpret simple checks of tax returns against third-party information or various notifications sent by the IRS as an audit. This may partially explain the overestimation of the audit rates.

The second issue is related to determining the typical penalty rate. There are uncertainties related to the actual penalties imposed depending on the circumstances of each case. The penalty rate can be as high as 75% and as low as 20%. Moreover, only statutory penalty rates were considered in this chapter. Actual economic costs of being caught evading taxes may be much higher than the statutory penalties (e.g., loss of income if time away from work is required, hourly cost of a tax preparer, travel to an IRS office, etc.).

Third, just like any self-reported income data, the family income data used in this chapter is likely to be subject to numerous inaccuracies.[52] These inaccuracies are due to various reasons such as respondent's lack of knowledge, problems recalling the amount and sources of income earned during a year, and mathematical errors associated with adding income from different sources and/or earned by every household member. Such inaccuracies generally produce underestimated values of income (Moore et al., 2000). This underestimation of income may contribute to the overestimation of effective tax rates observed in this study. Yet, it cannot fully explain the overestimation since the estimated effective tax rates in the US do not dramatically change as income increases (see **Table 2.3**).

Additionally, the structure of the income question in the survey required respondents to select out of 17 income brackets that best represents their total family income. While this structure may have induced more honest answers, it reduced variation in the income variable, as well as in the estimates of the actual marginal and effective tax rates. Finally, the assumptions made while estimating the actual marginal and effective tax rates probably further reduced the accuracy and the variation of the corresponding variables.

The analytical methods employed in this chapter have their own set of limitations. First, these tests and models are based on a multitude of assumptions, some of which may or may not be justifiable. As an example, it was assumed that the most of the reported regression models

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[52] Moore, Stinson, and Welniak (2000) provide a good review of studies on income measurement errors in surveys.

were correctly specified. This assumption was checked with tests like Link test and Ramsey's RESET test. However, they are not reported in this chapter since alternative model specifications usually generated qualitatively similar outcomes. In other words, the results were generally robust across different models.

Second, all considered models mostly had low explanatory power. This was not a surprise since there were weak, or at best, moderate correlations between the independent variables and the perceptions of the audit, penalty and tax rates. This means that these perceptions are also shaped by some other factors that were not examined in this study.

Concluding Remarks

This chapter explored how well people's perceptions of the audit, penalty and tax rates reflect the actual values of these rates. It also examined how these perceptions are correlated with various personal characteristics, experiences, attitudes and beliefs. The next chapter will analyze the potential impact of these perceptions on tax evasion. Tax evasion elasticities will be calculated with respect to perceived audit rates, perceived penalties and perceived effective tax rates. The third chapter will also study if tax evasion is influenced by perceived norms and attitudes toward tax fairness, public goods and services.

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Chapter 3: Tax Evasion Elasticities with Respect to Perceived Audit, Penalty and Tax Rates

Introduction

This chapter focuses on subjective probabilities of evasion and how these probabilities are related to perceived effective tax rate, perceived audit rate and perceived penalty rate. Specifically, the effect of these rates on the evasion probabilities are measured. This chapter also tests some theoretical conclusions derived from the A-S model, which have been discussed in detail in Chapter 1. Some other relevant hypotheses, not based on the A-S model, are examined as well. The chapter addresses the following specific research questions:

4) How do perceptions of effective tax rates, audit rates and penalty rates relate to tax evasion? What are the evasion elasticities with respect to perceived tax, audit and penalty rates?
5) In terms of changes in evasion rates, are taxpayers more responsive to a tax increase than to a tax decrease?
6) Is there any evidence suggesting that taxpayers use expected penalties in their decision-making process about tax evasion?
7) To what extent is tax evasion impacted by perceived norms and attitudes toward tax fairness, public goods and services? Is tax evasion associated with personal and social network characteristics?

To explore these questions, two econometric models of the evasion probability were developed and estimated using data from the RAND ALP Tax Evasion Survey. These analyses lead to several key findings. First, the evasion probabilities are not very responsive to changes in tax, audit and penalty rates. The evasion probabilities are mostly inelastic[53] over a wide range of these rates. Second, there is evidence suggesting that, in terms of changes in evasion rates, taxpayers seem to be more responsive to tax increases than to tax decreases. Third, contrary to the A-S model predictions, the analyses did not find any evidence that taxpayers, whose tax rates is larger than their expected penalty rate, are more likely to evade taxes. Additionally, the expected penalty was not found to be significantly associated with the evasion rates. Finally, no significant associations were observed between the evasion rates and most of the considered variables for respondents' personal and social-network characteristics, experiences, attitudes and beliefs.

The chapter starts with a section describing methods and data used for the analyses. The next section presents descriptive statistics for point elasticities individually estimated for the

[53] The word "inelastic" is used throughout the chapter as an economic term, indicating that the absolute value of an elasticity estimate is less than 1.

respondents. The purpose of this section is to provide preliminary estimates and detect any problems associated with the data. The two subsequent sections test two different hypotheses related to the evasion rates. The next section describes two different regression models of the evasion rates. These models are used in the penultimate section to estimate evasion rate elasticities with respect to tax, audit and penalty rates. The chapter is concluded by a discussion of the findings and the limitations of the analyses.

Data and Methods

Data

The analyses on tax evasion elasticities also draw upon the ALP Tax Evasion Survey data. The dataset contains variables describing respondents' personal and social network characteristics, personal experiences, attitudes and beliefs. These variables were described in detail in Chapter 2.

The primary variable of interest for this chapter is the *perceived evasion rate*. The survey question for this variable was following:

> *"Now consider people like you. In a typical year, out of 100 people like you, how many intentionally underreport their taxes?"*

The responses to this question were treated as baseline evasion rates, E_0. Each respondent was also asked six similar questions that had varying hypothetical conditions. In these six additional questions, the respondents were asked what the evasion rate would be if the current tax, audit, and penalty rates were changed by a certain percentage.

The first two of these questions were about the evasion rate under different tax rates (E_1 and E_2). Some respondents received two questions with the tax rates increased by 50% and 100%. The others were asked two questions with the tax rates decreased by 25% and 50%. The respondents were randomly assigned to either the tax-increase or the tax-decrease questions, with the exceptions of cases when respondents' baseline evasion rates were at the extremes, i.e. 0 and 100%. If a respondent's baseline evasion rate was zero, then she was given the tax-increase questions. On the other hand, if the baseline evasion rate was 100%, then she received the tax-decrease questions.

The next two questions were about the evasion rate under audit rates twice and three times as high as the current one (E_3 and E_4). However, these two questions were not asked if a respondent's baseline evasion rate was zero. It was assumed that if under lower audit rates the number of evaders is zero, then under the higher rates that number would still be zero.[54] In other words, if under the current deterrence conditions no one evades, then under stricter deterrence conditions there would be no evaders too.

[54] However, in these cases, E_3 and E_4 were still treated as missing in the analyses.

The last two evasion rate questions were questions with either increased or decreased penalties (*E_5* and *E_6*). About half of the respondents received the questions with the penalty rate 50% and 100% higher. The other half had the questions with penalty rate being 50% and 25% lower. This assignment of the questions was also mostly random. Yet, there were some exceptions again. When respondents' baseline evasion rates were zero, they were asked the questions with the penalty-rate decrease. And if respondents' baseline evasion rates were 100%, then they received the questions with the penalty-rate increase.

The design of these questions treats the evasion rates as a respondent's subjective probabilities that he/she will underreport taxes under different conditions. Thus, the questions provide seven different evasion probability estimates for each respondent (one baseline and six hypothetical scenarios), once the rates are converted into fractions or percentages. The exact wording of these questions, as well as the skip patterns applied to them, can be found in **Appendix D**.

As was already mentioned in the previous chapter, the dataset also contains variables on the perceptions of the federal tax (*T*), audit (*A*) and penalty (*P*) rates.[55] These rates served as the baseline (T_0, A_0 and P_0). Using these baseline rates and the percentage changes applied to them in the six hypothetical evasion rate questions, I calculated two additional tax rates, T_1 and T_2; two additional audit rates, A_3 and A_4; and two additional penalty rates, P_5 and P_6. A_3 and A_4 were capped at 1 (or 100%) if they exceeded 1[56] since audit rate cannot be greater than 1 (or 100%). After these calculations, each respondent typically had the following set of evasion, tax, audit and penalty rates:

Table 3.1: A Respondent's Set of Evasion, Tax, Audit and Penalty Rates by Hypothetical Scenarios

Scenarios	Evasion Rate	Tax Rate	Audit Rate	Penalty Rate
Baseline	E_0	T_0	A_0	P_0
1	E_1	$T_1 = 1.5*T_0$ or $T_1 = 0.75*T_0$	$A_1 = A_0$	$P_1 = P_0$
2	E_2	$T_2 = 2*T_0$ or $T_2 = 0.5*T_0$	$A_2 = A_0$	$P_2 = P_0$
3	E_3	$T_3 = T_0$	$A_3 = 2*A_0$	$P_3 = P_0$
4	E_4	$T_4 = T_0$	$A_4 = 3*A_0$	$P_4 = P_0$
5	E_5	$T_5 = T_0$	$A_5 = A_0$	$P_5 = 1.5*P_0$

55 These rates and the evasion rates were converted into fractions or percentages before conducting the analysis of this chapter.

56 This happened when the respondents' baseline perceived audit rates were high. For example, if a respondent had a baseline audit rate, $A_0 = 0.6$, then doubling and tripling it will make A_3 and A_4, respectively, greater than 1. There were 46 respondents whose baseline perceived audit rate was greater than 0.5 and 172 respondents whose baseline perceived audit rate was greater than 0.33. Doubling and tripling these rates produced audit rates above 1. Few respondents also had tax rates T_1 or T_2 greater than 1. But since theoretically it is possible to have a tax rate greater than 100%, these tax rate values were not capped at 1.

				or $P_5 = 0.5*P_0$
6	E_6	$T_6 = T_0$	$A_6 = A_0$	$P_6 = 2*P_0$ (or $P_6 = 0.75*P_0$)

Methods

This data allows estimation of the impact of changes in perceived tax, audit and penalty rates on the evasion rates. In order to do this, the following point elasticity formula was used:

$$\varepsilon_{y,x} = \frac{\Delta y}{\Delta x}\frac{x}{y} \qquad (3.1)$$

Where y was a starting point for evasion rate and Δy was the change in the evasion rate relative to the starting point; x was a starting point for either perceived tax, perceived audit or perceived penalty rate and Δx was the change in the perceived rate relative to the starting point. For example, if the baseline scenario is taken as a starting point, then the evasion rate elasticity with respect to the perceived tax rate will be:

$$\varepsilon_{E,T} = \frac{\Delta E}{\Delta T} * \frac{T_0}{E_0} = \frac{(E_1 - E_0)}{(T_1 - T_0)} * \frac{T_0}{E_0} \qquad (3.2)$$

Given that there were three scenarios for the tax rates (one baseline and two hypothetical scenarios), three different elasticities were estimated for evasion between 1) the baseline and 1st hypothetical scenarios (eET10[57]); 2) the baseline and 2nd hypothetical scenarios (eET20); 3) 1st and 2nd hypothetical scenarios (eET21). Similarly, three different evasion rate elasticities were estimated for the perceived audit rate (eEA30, eEA40 and eEA43); and another three for the perceived penalty rate (eEP50, eEP60 and eEP65). All these elasticities were calculated for each respondent.

While these elasticity estimates are useful for describing individual responses to changes in tax, audit and penalty rates, they have some limitations. First, the estimates are not defined when the baseline evasion rate or perceived tax, audit and penalty rates are zero (i.e., $E_0 = 0$ or $T_0 = 0$, $A_0 = 0$, $P_0 = 0$). Second, this method does not control for other variables that may mitigate or augment the response.

One way to address these limitations, at least partially, is to develop regression models for the evasion rate with tax, audit and penalty rates as key independent variables, and then use these models to estimate the elasticities. Two types of such models were selected for that purpose: 1) a *linear mixed effects* (*ME*) *model* with random intercepts and coefficients on perceived tax, audit and penalty rates, and with covariance between the slopes and the intercepts; 2) a *fractional response model* (*FRM*) similar to the one described by Papke and Wooldridge (2008), but with a complementary log-log link function.[58]

The model types were chosen based on certain selection criteria. First, all things equal, the model should be relatively simple, and it should be relatively easy to interpret its results.

[57] In eET10, the small *e* is for "elasticity", the capital *E* is for "evasion", the capital *T* is for tax, number 1 is for scenario 1, and 0 is for the baseline scenario. Similarly, in eEA30, eEA40, eEA43, eEP50, eEP60 and eEP65, the capital *E* is for "evasion", the capital *A* and *P* are for audit and penalty, respectively. The digits show the scenario numbers, with the last digit indicating the starting point.

[58] STATA code for the models is available upon request.

Second, the model should be of higher quality as measured by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. The models with the lower AIC and BIC values were preferred. Finally, the model should have some theoretical basis and there should be a methodological precedent of using a similar model in similar circumstances.

The ME model fared particularly well in terms of the first two selection criteria. It assumes a linear structure, which make the regression coefficients easy to interpret. It also had one of the lowest AIC and BIC values.[59] The main disadvantage of the linear ME model is that it may predict evasion rates below 0 or above 1, which are outside the logical boundaries. Besides, while the linear model might be a good approximation, the relationship between evasion probabilities and perceived tax, audit and penalty rates is likely to be non-linear.[60] Vardavas et al. (2019) hypothesize that the said relationship is likely to be an asymmetric S-curve.

These disadvantages of the ME model were handled with the FRM. The FRM is estimated with a generalized estimating equation (GEE) method. The model had a binomial distribution as a family distribution and a complementary log-log function as a link function. The complementary log-log function assumes an asymmetric S-curve relationship between evasion rates and the independent variables. Moreover, the FRM bounds the predicted evasion rates between 0 and 1. Because of this, the FRM also fairs well on the third criterion. However, the FRM is weaker on the first criterion, as the FRM model coefficients are not simple to interpret.

In addition to the elasticity calculations, t-tests for the differences between the means of two independent groups were performed. This test was employed to see if there were any differences in the strength of the responses to tax rate increase and tax rate decrease. A similar t-test was also conducted for the penalty rates.

Point Elasticities

Estimated point elasticities for evasion rates with respect to tax rates were mostly positive, as expected, including mean and median of the tax elasticities (see **Table 3.2.a**). This suggests that increasing tax rates (or perceived tax rates) are likely to be associated with increased evasion rates. This finding is consistent with the empirical evidence from some other studies (Alm, Deskins, & McKee, 2009; Alm, Jackson, & McKee, 1992; Clotfelter, 1983; Frey & Feld, 2002; Park & Hyun, 2003).

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[59] A fixed-effects model had the lowest AIC and BIC values among the considered types of regression models. This fixed-effects model was also preferred to random effects model based on the results of the Hausmann test. However, this model has one main disadvantage compared to the ME model. While the ME model allows the inclusion of independent variables that are static over the scenarios (like age, gender, and employment status), the fixed effects model doesn't. For this reason, the mixed effects model was preferred.

[60] At the very least, most of the probability models (like probit, logit and complementary log-log models) assume an S-curve relationship.

Table 3.2.a: Tax Elasticities of the Evasion Rate

Point Elasticities	Unweighted								With Sampling Weights	
	n	Mean	SD	Min	1st Quartile	Median	3rd Quartile	Max	Mean	95% CI
eET10	782	2.06	9.63	-76.0	0.0	1.00	2.4	118.0	2.20	(1.19; 3.21)
eET20	781	1.12	5.20	-58.0	0.0	0.67	1.5	49.0	1.06	(0.55; 1.58)
eET21	822	0.50	3.43	-19.5	0.0	0.00	1.2	72.0	0.33	(-0.43; 1.10)

NOTES: 1) In eET10, eET20 and eET21, the small *e* is for "elasticity", the capital *E* is for "evasion", the capital *T* is for "tax", the digits are scenario numbers. For example, 20 means that the data from scenario 2 and scenario 0 (the baseline scenario) was used in the calculation. The 1st digit shows the end point, while the 2nd indicates the starting point. 2) Sample sizes are different since the point elasticities were not defined for every respondent because of either missing values or division by zero.

Unlike the tax elasticity estimates, the typical sign of the audit point elasticities was less definitive, as evident from **Table 3.2.b**. While mostly negative as anticipated, the median audit elasticity estimates were close to zero. The point elasticities were also mainly clustered around zero. Although more than half of the estimates were zero or negative, there were many positive audit elasticity estimates too. Over 47% of eEA30, about 39% of eEA40 and about 19% of eEA43 values were positive.[61] As shown, a substantial portion of the responses to audit rate changes is inconsistent with the theory, which predicts that the evasion rate will decline if the audit rate is increased.

Table 3.2.b: Audit Elasticities of the Evasion Rate

Point Elasticities	Unweighted								Weighted	
	n	Mean	SD	Min	1st Quartile	Median	3rd Quartile	Max	Mean	95% CI
eEA30	848	0.610	3.71	-1.0	-0.50	0.00	0.33	49.0	0.91	(0.3; 1.51)
eEA40	816	0.300	2.00	-0.5	-0.33	-0.12	0.13	24.5	0.43	(0.1; 0.75)
eEA43	816	-0.080	1.94	-29.0	-0.34	-0.10	0.00	14.0	-0.11	(-0.44; 0.22)

NOTES: 1) In eEA30, eEA40 and eEA43, the small *e* is for "elasticity", the capital *E* is for "evasion", the capital *A* is for "audit", the digits are scenario numbers. For example, 40 means that the data from scenario 4 and scenario 0 (the baseline scenario) was used in the calculation. The 1st digit shows the end point, while the 2nd indicates the starting point. 2) Sample sizes are different since the point elasticities were not defined for every respondent because of either missing values or division by zero.

The distributions of the penalty point elasticities were similar to those of the audit elasticities. The medians of the penalty elasticities were zero, and the absolute value of the means were less than one (see **Table 3.2.c**). The penalty elasticity estimates were also mainly clustered

[61] The distributions of eEA30 and eEA40 estimates were severely skewed to the right as well. The distribution of eEA43 values were also severely skewed, but it was skewed to the left.

around zero[62] and were mostly negative as predicted by the theory. However, over 43% of eEP50, 40% of eEP60 and about 22% of eEP65 estimates were positive. These positive estimates are inconsistent with the standard economic theory, since higher penalties are usually expected to be associated with lower evasion rates holding everything else constant.

Table 3.2.c: Penalty Elasticities of the Evasion Rate

Point Elasticities	Unweighted								Weighted	
	n	Mean	SD	Min	1st Quartile	Median	3rd Quartile	Max	Mean	95% CI
eEP50	839	-0.01	6.29	-58.0	-1.00	0.0	0.50	97.0	0.24	(-0.59; 1.08)
eEP60	806	-0.97	8.52	-196.0	-0.67	0.0	0.50	24.0	-0.94	(-1.87; -0.02)
eEP65	871	0.20	3.22	-3.0	-0.67	0.0	0.00	48.0	0.46	(-0.01; 0.94)

NOTES: 1) In eEP50, eEP60 and eEP65, the small *e* is for "elasticity", the capital *E* is for "evasion", the capital *P* is for "penalty", the digits are scenario numbers. For example, 60 means that the data from scenario 6 and scenario 0 (the baseline scenario) was used in the calculation. The 1st digit shows the end point, while the 2nd indicates the starting point. 2) Sample sizes are different since the point elasticities were not defined for every respondent because of either missing values or division by zero.

These inconsistent responses may partially stem from lapses of memory. Because the baseline questions for the hypothetical audit and penalty scenarios occurred later in the survey than their respective baseline questions, some respondents may have forgotten what their responses to the baseline evasion rate question was when they received hypothetical scenario questions. This forgetfulness may have made them more susceptible to providing inconsistent answers to the scenario questions. There is some evidence supporting this claim. The respondents were reminded of their baseline evasion rate just before they received the tax-related hypothetical questions, but there were no such reminders for the audit- and penalty-related hypothetical questions. Not surprisingly, the respondents gave more inconsistent responses[63] to the audit and the penalty questions than to the tax questions.

Another potential source of these inconsistencies is incomprehension. The hypothetical questions asked the respondents to imagine scenarios when certain elements are changed by certain percent like "the penalty rate was 50% higher than it currently is" or "tax rates are 25% lower than what they currently are." Since the questions required a fair amount of numeracy skills, they might have been difficult to process for some respondents who lack those skills. Such respondents would have been more prone to answering the questions inconsistently. Indeed, there is a strong association between the inconsistent responses and an 8-item

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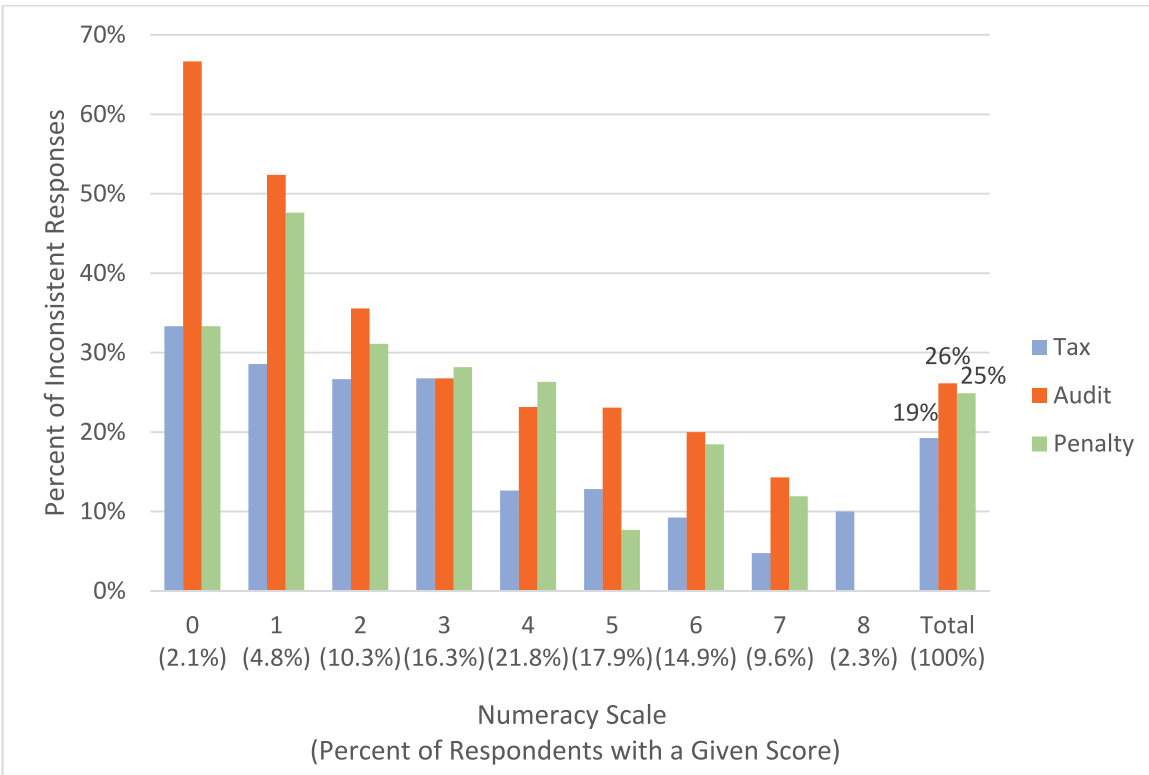
62 The distributions of the penalty point elasticities were also severely skewed. While the distributions of eEP50 and eEP65 were skewed to the right, eEP60 was skewed to the left.

63 The responses were flagged as inconsistent if change in the evasion rate was by more than 5 percentage points in a direction opposite to what the standard theory or common sense predicts. For example, if a respondent indicated that 40 out of 100 people like her intentionally underreport their taxes in the baseline question and responded that 46 out of 100 people like her would underreport their taxes if the audit rate is twice as high, then her response was tagged as inconsistent.

numeracy scale developed by Weller et al. (2013). This scale, which was fielded on prior ALP surveys, ranges from 0 to 8, with higher scores meaning better numeracy skills.[64] As illustrated in **Figure 3.1**, respondents with the lower scores (i.e., with lower numeracy skills) were substantially more likely to provide inconsistent responses on the Tax Evasion Survey. This association is also confirmed with χ^2 tests for independence between the numeracy scale and whether a respondent had an inconsistent response. The χ^2 values were 21.89 (with p-value = 0.005), 26.25 (with p-value = 0.001) and 28.77 (with p-value < 0.001) for tax, audit and penalty scenario questions, respectively.

Figure 3.1: Inconsistent Responses by Numeracy Scale and by Tax, Audit and Penalty Scenarios



NOTE: The numeracy scale data was available only for a sub-sample of 436 ALP Tax Evasion Survey respondents. Therefore, the percentages by scale are based on this sub-sample only. The total percentages of the inconsistent responses are for the entire sample.

Furthermore, note that none of the people with the highest numeracy score (8) provided inconsistent response to the audit and penalty questions. On the other hand, while respondents with low numeracy scores ($\leq$ 3) represented about one third of all respondents, they were responsible for nearly half of the inconsistent responses. Their share in the inconsistent responses to the tax, audit and the penalty questions were over 56%, about 47% and almost 50%, respectively.

[64] Unfortunately, these data are available only for 436 out of 1029 respondents to the ALP Tax Evasion Survey.

The Asymmetric Response Hypothesis

It was hypothesized in Chapter 1 that in terms of tax compliance, taxpayers' reaction to tax rate decreases may not be as strong as their reaction to tax increases. This hypothesis is in accordance with the concept of loss aversion. Due to the loss aversion, taxpayers will lose more utility from a tax hike than they will gain from an equal amount of tax cut. Such asymmetric change in utility can potentially produce asymmetric responses by taxpayers to tax rate increases and decreases. This asymmetric response hypothesis (ARH) is formally stated below:

> *Asymmetric Response Hypothesis:* In terms of changes in evasion rates, taxpayers are more responsive to tax increases than to tax decreases.

Given its potential policy implications, which were discussed in Chapter 1, it would be useful to test this hypothesis empirically. One simple way of testing the ARH is to compare the tax point elasticities between the respondents who were randomly assigned to the tax-increase and tax-decrease questions described in *Methods and Data* section. The comparison shows that the respondents who received the tax-increase questions have, on average, much higher elasticities than those who received the tax-decrease questions. As one can see from **Table 3.3**, the average tax elasticities are either close to one or greater than one for the former group of respondents, Group A. To put it differently, the evasion rate is typically unit elastic or elastic with respect to tax rate in the increasing tax rate group. On the other hand, the decreasing tax rate group (B) has mean elasticities close to zero, [65] which means that the evasion rate is relatively inelastic. The differences in the average point elasticities are statistically significant using a t-test, but the skewed elasticity data also violate the t-test assumption of the normal distribution of the variable.

Table 3.3: Asymmetric Response to Tax Rate Increase and Decrease (randomly assigned respondents only)

Mean Point Elasticities	Point Elasticity Formulas Used	With Sampling Weights: Group A: Increased Tax Rate	With Sampling Weights: Group B: Decreased Tax Rate	With Sampling Weights: Difference (p-value)	Unweighted: Group A: Increased Tax Rate	Unweighted: Group B: Decreased Tax Rate	Unweighted: Difference (p-value)
Elasticities:							
eET10	=(E1 - E0)/(T1-T0)*(T0/E0)	3.974	0.230	3.744 (<0.001)	4.169	-0.012	4.180 (<0.001)
eET20	=(E2 - E0)/(T2-T0)*(T0/E0)	2.326	-0.345	2.670 (<0.001)	2.388	-0.129	2.516 (<0.001)
eET21	=(E2 – E1)/(T2-T1)*(T1/E1)	0.979	-0.737	1.716 (0.049)	0.625	0.063	0.562 (<0.001)
Baseline Average:							
mean E0		0.221	0.277		0.223	0.250	
mean T0		0.242	0.293		0.237	0.249	

[65] Some of these average elasticities are negative, but there is not enough evidence to claim that they are different from zero. The 95% confidence intervals for the negative average tax elasticities in **Table 3.3** do include zero and positive values.

A more sophisticated way of testing the ARH is to use an econometric model with an interaction term. In this model, the dependent variable is the evasion rate and the independent variables include tax rate and the interaction term between tax rate and a binary variable indicating a respondent's group assignment. The marginal effect of this interaction term helps to detect the differences in response to tax rate increase and decrease. The main advantage of this method is that it allows to control for some other confounding factors like audit rates, penalties, personal characteristics and experiences. It also allows to estimate the differences in responses at specified values of the covariates.

Table 3.4 shows marginal effect (dydx) and elasticity (eyex) estimates based on two different models: an ME model and an FRM. Both models are discussed in detail later in the chapter. [66] The first model, ME, produced a sizable difference in the marginal effects. The average marginal effect of tax increase was almost twice (1.75 times) as large as the average marginal effect of tax decrease. The difference between the marginal effects was 0.23 and statistically significant. The difference in the elasticities estimated at the mean values was 0.276. Yet, both elasticity estimates were less than 1 in absolute terms, which indicates inelastic evasion rates with respect to tax rates.

The marginal effects estimated by the second model, the FRM, were substantially lower than those of the ME model. The difference between the average marginal effects was lower too (0.106) and was not statistically significant. Nevertheless, the marginal effect of tax increase was still almost twice (1.79 times) as large as the marginal effect of tax decrease. Moreover, the tax-increase group still had higher elasticity than the tax-decrease group.

Table 3.4: Differences in the Average Marginal Effects/Elasticities between Tax Rate Increase and Decrease Conditions

Estimation method	Marginal Effects (dydx) and Elasticities (eyex)[2)]	Tax Rate: Increased (Group A)	Tax Rate: Decreased (Group B)	Difference[1)] (Group A - Group B)	P-value for the Difference
Mixed-Effects Model	dydx	0.538	0.308	0.230	0.003
	eyex	0.610	0.334	0.276	n.e.
Fractional Response Model	dydx	0.240	0.134	0.106	0.189
	eyex	0.267	0.148	0.119	0.190

NOTES: 1) - The difference for the marginal effects in the ME model is the marginal effect for the interaction term. The reference group in this model was the respondents who received tax-decrease questions (Group B). The p-value is the one for the interaction term. 2) The following formula for the elasticities was used: eyex = (dydx)*x/y. The elasticities for the ME model are estimated at the mean values of the evasion and tax rates. For Group A, these values were $E = 0.260$ and $T = 0.295$, respectively. For Group B, the numbers were $E = 0.242$ and $T = 0.262$. 3) n.e. – not estimable. These are the means for

[66] The regression output for the models are also in **Appendix E**. In these models, the key regression coefficients were the ones for tax rate and for the interaction term between tax rate and the group assignment. The marginal effect for the tax variable was the estimated effect for the respondents who randomly received the tax-decrease questions since they were the reference group. The marginal effect for the interaction term was the difference between the marginal effects of the tax-increase and the tax-decrease groups.

all scenarios.

As demonstrated, there is some evidence supporting the asymmetric response hypothesis. The evasion rates are relatively more elastic when tax rates are increased than when they are decreased. To put it differently, people seem to be more responsive to tax rate increases than to tax rate decreases in terms of changes in the evasion rates.

Similar analyses conducted with the penalty rate found no significant evidence for analogous asymmetric response.

When the Expected Penalty Rate is Less Than the Tax Rate

The Allingham-Sandmo model predicts that a risk-averse taxpayer will underreport her income, if her tax rate is bigger than her expected penalty rate (i.e., the product of the penalty rate and the probability of detection) (Allingham & Sandmo, 1972). If this prediction is true, then one can expect that the evasion rate is likely to be higher for those taxpayers whose tax rates are bigger than their expected penalty rate. Therefore, it can be hypothesized that:

> *Hypothesis:* Taxpayers, whose tax rates are bigger than their expected penalty, have, on average, higher evasion rates than the others.

This hypothesis can also be tested with the ALP Tax Evasion Survey data, which also has a variable for a respondent's subjective probability of being caught if a taxpayer underreports her income.[67] By multiplying this probability to the perceived penalty rates, I estimated the expected penalty rate for each respondent. Then the expected penalties were compared with the perceived tax rates. Based on this comparison, the respondents were split into two groups: 1) those who have the expected penalty rate equal to or greater than their perceived tax rate; and 2) those whose expected penalty rates are less than their perceived tax rates.

These two groups have similar baseline evasion rates, which are presented in **Table 3.5**. Contrary to the hypothesis stated above, the first group have slightly higher average evasion rate.[68] Nonetheless, the difference between the average rates is not statistically significant.

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[67] The survey question for this variable was: "You previously stated that [X]% of taxpayers in the U.S. will intentionally underreport on their taxes. In a typical year, what percent of these people will be caught by the IRS?" While this question asks for the probability of detection for the overall population, the responses to it may still serve as a proxy variable for a respondent's probability of being caught. The mean response for this question was 18.85% with the standard deviation of 21.1%. The median was 10%, and the first and the third quartiles were 5% and 25%, respectively.

[68] The median evasion rate for this group was also higher than for the second group. For Group 1 (*Expected Penalty* $\geq$ *Tax*) and Group 2 (*Expected Penalty* $<$ *Tax*) the median values were 0.15 and 0.10, respectively.

Table 3.5: Average Baseline Evasion Rates by Whether or Not the Expected Penalty is Less Than Tax

Groups	n	Baseline Evasion Rates: Mean	Baseline Evasion Rates: Standard Error	Average Difference (Group 2 - Group 1)	t statistic	p-value (two-tailed)
Unweighted:						
Group 1: *Expected Penalty* $\geq$ *Tax*	140	0.216	0.0204	-0.011	-0.52	0.601
Group 2: *Expected Penalty* $<$ *Tax*	853	0.205	0.0076			
Weighted:						
Group 1: *Expected Penalty* $\geq$ *Tax*	--	0.254	0.0387	-0.045	-1.08	0.280
Group 2: *Expected Penalty* $<$ *Tax*	--	0.210	0.0139			

Regression analyses with the panel data also did not produce any significant evidence supporting the hypothesis. In these analyses, the dependent variable was the evasion rate. The key independent variable was an indicator variable equal to 1 if the expected penalty rate was less than tax rate, and to 0 if otherwise. In all considered regression models, the coefficients for this indicator variable were close to zero and statistically insignificant (see **Table 3.6**).

Table 3.6: The Regression Coefficients for the Indicator Variable[69] for Whether or Not the Expected Penalty is Less Than Tax

Estimation Method	Coefficient	S.E.	p-value	95% Confidence Interval	
Mixed-Effects model	0.006	0.014	0.676	-0.022	0.034
Fractional Response Model*	-0.029	0.088	0.743	-0.202	0.144
Fixed-Effects Model	0.036	0.023	0.118	-0.009	0.080

NOTE: * - For the sake of comparison, the average marginal effect, instead of the regression coefficient, is reported for the fractional response model, which is a non-linear model unlike the other ones.

To sum up, there was no evidence suggesting that taxpayers whose expected penalty is lower than their tax have higher evasion rates. These taxpayers seem to have about the same evasion probabilities as the rest. Furthermore, I did not find any significant evidence that the expected penalty rate is associated with the evasion rate. Regression models of the evasion rate generally had statistically insignificant coefficients for the expected penalty, even though the coefficients usually had the expected negative sign. Two of these models are presented in **Appendix F**.

[69] This variable was the only independent variable in the presented regression models. Adding other independent variables to the models did not significantly change the results.

Regression Models of the Evasion Rate

Two other regression models of the evasion rate were considered in order to estimate the marginal effects, as well as, the elasticities of tax, audit and penalty rates. While tax, audit and penalty rates were the key independent variables, some other variables were also included to control for respondents' personal and social-network characteristics, experiences, attitudes and beliefs. All these variables and their brief description are presented in **Table 3.7**.

Table 3.7: List of Covariates Used in the Regression Analysis and Their Brief Description[70]

Covariates	Description	Mean (SD) or %*
Perceived Rates and the Group Assignment:		
Tax rate	Perceived federal income tax rate	0.239 (0.143)
randomtaxincrease	=1 if randomly received the tax-increase questions; 0 if randomly received tax decrease questions.	42.08%
randomtaxincrease*Tax rate	interaction term between randomtaxincrease and perceived tax rate	--
Audit rate	Perceived audit rate	0.200 (0.169)
Penalty rate	Perceived penalty rate	0.389 (0.907)
Personal Characteristic:		
Age	in years	56.5 (13.8)
Black-African American	= 1 if Black-African American; 0 otherwise	8.45%
Native American	= 1 if Native American; 0 otherwise	1.36%
Asian	= 1 if Asian; 0 otherwise	2.33%
Other Race	= 1 if Other race; 0 otherwise	5.83%
hispaniclatino	= 1 if Hispanic/Latino; 0 otherwise	14.67%
male	= 1 if male; 0 otherwise	44.12%
married	= 1 if married; 0 otherwise	59.38%
education	= 1 if has Bachelor's degree and above; 0 otherwise	49.76%
foreignborn	= 1 if foreign born; 0 otherwise	10.79%
Marginal Tax Rate	Marginal federal income tax rate estimated based on the survey questions on family income. Measured in fractions, i.e., range $\in [0;1]$.	0.172 (0.079)
self-employed	= 1 if self-employed; 0 otherwise	17.30%
Social Network Characteristics:		
prop_altersaudited	Proportion of alters who are believed to be audited	0.029 (0.083)
prop_alters_talkTaxes	Proportion of alters with whom the respondent has talked or consulted with about taxes in the past 5 years	0.279 (0.280)
prop_alterselfemployed	Proportion of alters who are self-employed	0.206 (0.225)
Experiences:		
hheveraudited	= 1 if self or spouse has ever been audited; 0 otherwise	20.21%
haventfiledtaxes	= 1 if ever filed taxes or had someone else to file taxes for them; 0 otherwise	3.11%
preptaxesself	= 1 if prepares taxes himself/herself; 0 otherwise	39.55%
Attitudes, beliefs, and views:		

70 More detailed descriptive statistics are available in **Appendix G**.

prob_deduction	Respondents' subjective probability of them claiming a questionable tax deduction	0.294 (0.319)
actor_more	= 1 more likely or somewhat more likely to fully report taxes if a famous actor is known to evade taxes; 0 otherwise.	20.99%
freeriding_never	Total number of "Never ok" responses to 5 separate questions about engaging in 5 different free-riding activities. Maximum is 5 (it is never ok to engage in all these free-riding activities); minimum is 0 (the respondent thinks that it is always ok or sometimes ok to engage in all these 5 free-riding activities). These free-riding activities are: 1. Regularly listen to public radio without ever contributing; 2. Illegally copying, downloading, or streaming movies; 3. Have a dog but not getting it spayed or neutered; 4. Avoid getting the flu vaccine; 5. Avoid paying all of the income tax that you owe.	2.54 (1.15)
freeriding_percentage	Average score for 5 questions about percentage of people like respondents who engage in 5 different free-riding activities. These free-riding activities are the same as described in the entry for ***freeriding_never***.	49.8 (17.73)
worthpayingtaxes	= 1 if thinks that public goods and services worth paying taxes for; 0 otherwise	56.76%
importancetaxbenefits	Relative importance of *benefits and public service supported by taxes* when the respondent thinks about taxes and paying his/her taxes. Maximum is 100 points; more points more important.	24.8 (19.98)
importancemoraloblig	Relative importance of *a moral obligation to correctly report and pay taxes* when the respondent thinks about taxes and paying his/her taxes. Maximum is 100 points; more points more important.	23.7 (25.11)

NOTE: * - No sampling weights were used in calculating these descriptive statistics. Therefore, they might be slightly different from the corresponding numbers reported elsewhere in the chapter. Percentages are calculated based on the entire sample.

Both models, the ME model and the FRM, produced positive and statistically significant coefficients for tax rate (see **Table 3.8**). However, as was discussed earlier, the ME model yielded larger average marginal effect of tax rate than the FRM. For taxpayers who face a tax rate decrease, the average marginal effect was 0.308 in the ME model versus 0.134 in the FRM model. In other words, holding everything else constant, each percentage point decrease in the perceived tax rate is accompanied with 0.308 and 0.134 percentage points reduction in the evasion rate according to the ME model and the FRM, respectively. In the ME model, for taxpayers experiencing tax rate increase, *ceteris paribus*, each percentage point increase in the tax rate is associated with 0.538 percentage points increase in the evasion rate compared to 0.240 for the FRM.

Table 3.8: Two Regression Models of the Evasion Rate[71]

Independent Variables	Mixed-Effects Model			Fractional Response Model			
	Coef.	S.E.	p-values	Coef.	S.E.	p-values	Average Marginal Effects
Perceived Rates and the Group Assignment:							
Tax rate	0.308	0.0619	<0.001	0.665	0.3238	0.040	0.134
randomtaxincrease	-0.022	0.0223	0.325	0.028	0.1526	0.856	0.033
randomtaxincrease*Tax rate	0.230	0.0769	0.003	0.432	0.3991	0.279	0.106
Audit rate	-0.046	0.0232	0.045	0.115	0.1648	0.484	0.024
Penalty rate	-0.070	0.0237	0.003	-0.011	0.0093	0.230	-0.002
Personal Characteristic:							
Age	-0.001	0.0006	0.341	0.000	0.0029	0.948	0.000
Black-African American	0.011	0.0258	0.662	-0.046	0.1347	0.733	-0.010
Native American	0.087	0.0664	0.191	--	--	--	--
Asian	-0.057	0.0456	0.210	-0.424	0.2251	0.060	-0.078
Other Race	0.033	0.0391	0.399	0.244	0.1721	0.156	0.055
hispaniclatino	0.002	0.0261	0.938	-0.080	0.1362	0.559	-0.017
male	0.028	0.0151	0.069	0.030	0.0913	0.741	0.006
married	-0.024	0.0164	0.147	0.019	0.1031	0.857	0.004
education	-0.013	0.0159	0.418	-0.021	0.1085	0.847	-0.004
foreignborn	0.020	0.0279	0.472	0.200	0.1527	0.190	0.044
Marginal Tax Rate	-0.136	0.1092	0.214	-0.716	0.6264	0.253	-0.151
self-employed	0.011	0.0198	0.576	0.012	0.1570	0.939	0.003
Social Network Characteristics:							
prop_altersaudited	0.049	0.1268	0.698	0.698	0.4442	0.116	0.147
prop_alters_talkTaxes	-0.028	0.0263	0.294	-0.241	0.1700	0.156	-0.051
prop_alterselfemployed	0.025	0.0375	0.502	0.463	0.1904	0.015	0.097
Experiences:							
Hheveraudited	-0.024	0.0183	0.182	-0.260	0.1217	0.032	-0.052
haventfiledtaxes	0.079	0.0544	0.148	0.006	0.1701	0.973	0.001
preptaxesself	-0.029	0.0153	0.058	-0.118	0.0974	0.226	-0.025
Attitudes, beliefs, and views:							
prob_deduction	0.105	0.0253	<0.001	0.605	0.1340	<0.001	0.127
actor_more	0.034	0.0185	0.064	0.225	0.1136	0.047	0.049
freeriding_never	-0.014	0.0070	0.048	-0.053	0.0349	0.131	-0.011
freeriding_percentage	0.001	0.0004	0.084	0.006	0.0023	0.005	0.001
worthpayingtaxes	-0.008	0.0151	0.594	-0.114	0.0915	0.213	-0.024
importancetaxbenefits	0.000	0.0004	0.923	0.003	0.0021	0.200	0.001
importancemoraloblig	0.000	0.0003	0.273	0.000	0.0021	0.963	0.000

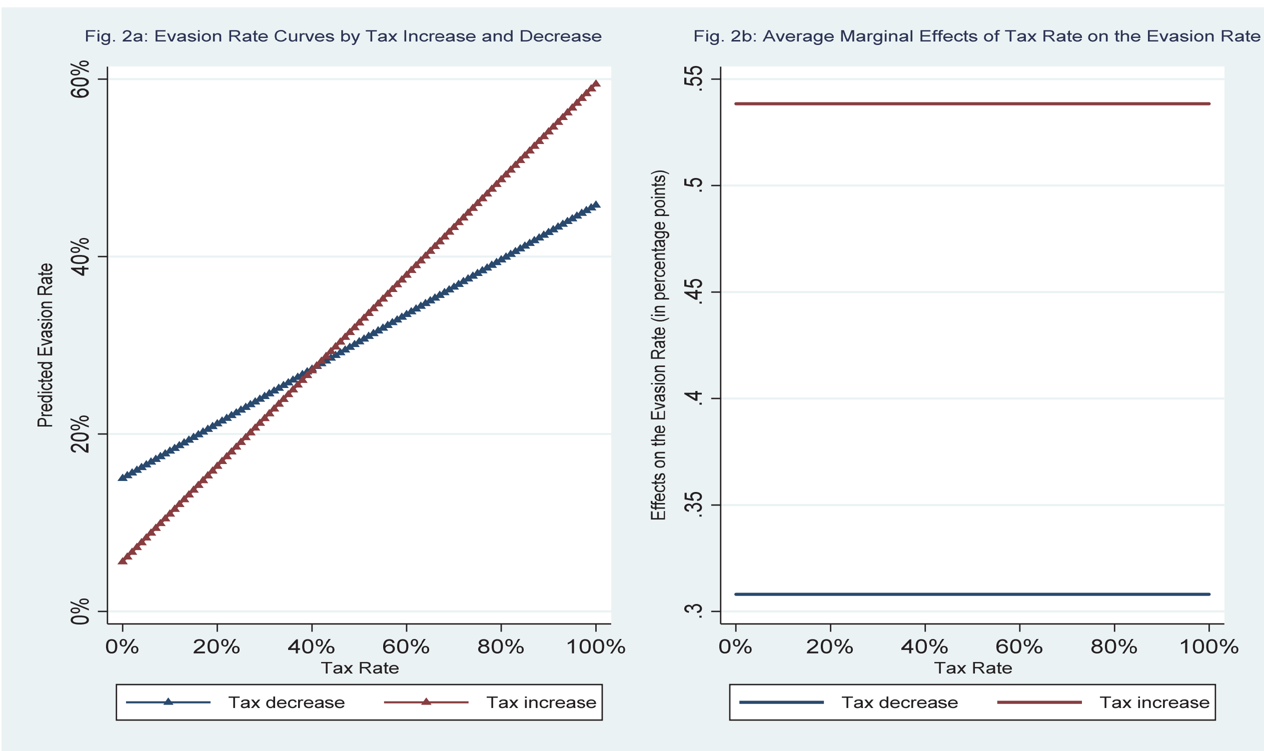
[71] These models were estimated by using the sampling weights. The same models were also run without the weights. The output for the models without the sampling weights can be found in **Appendix H**.

constant	0.215	0.0556	<0.001	-1.894	0.2939	0.000	--
Num. of obs. = 5,159		Wald chi2(30) = 285.08		Num. of obs. = 5,084		Wald chi2(29) = 210.44	
Num. of resp. = 752		p-value < 0.001		Num. of resp. = 741		p-value < 0.001	

NOTE: In the FRM, the binary variable for Native Americans were dropped out of the analysis because of collinearity.

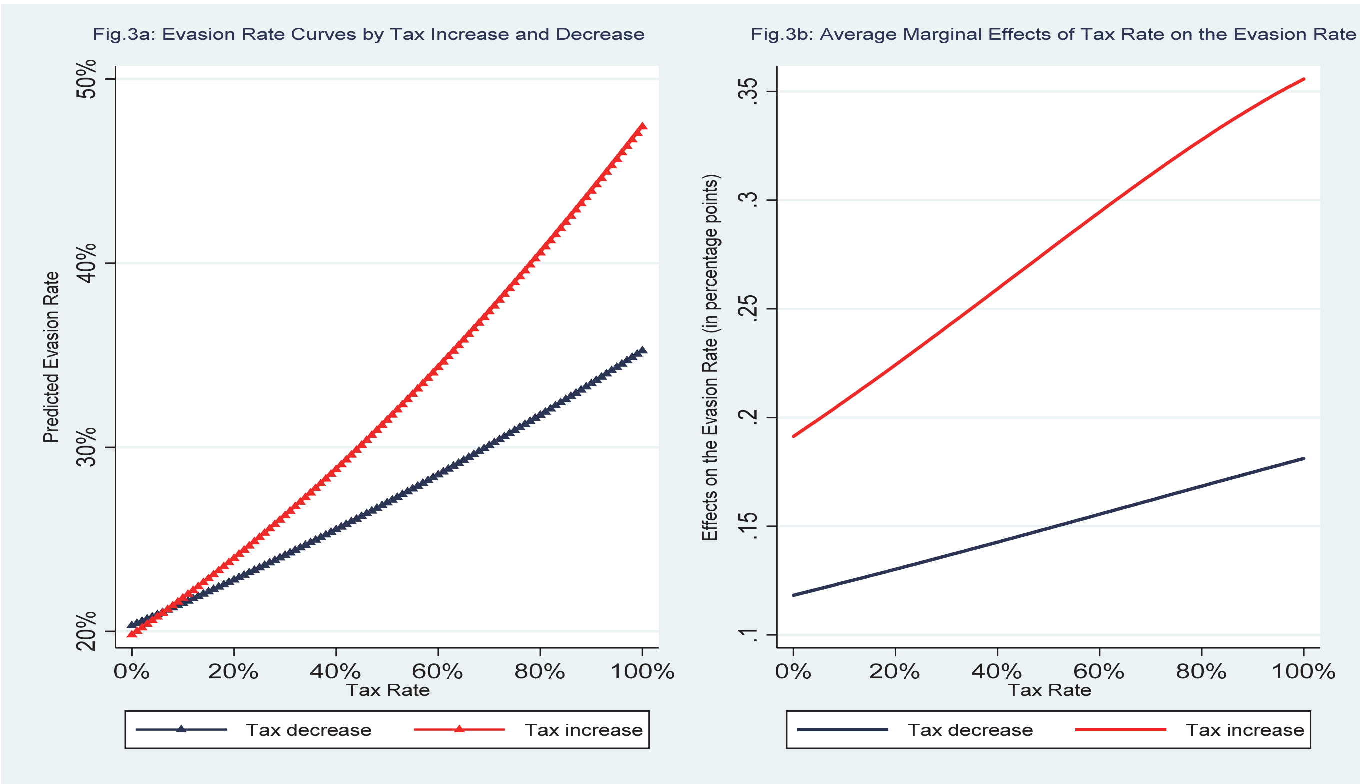
In both models, the coefficient for *randomtaxincrease* variable was small and not significant. This finding suggests that the evasion curve intercept for the respondents who were randomly assigned the tax-increase questions is similar to the one for those who received the tax-decrease questions. The interaction term between *randomtaxincrease* and tax rate, however, had a positive and significant coefficient in the ME model. The positive coefficient means that the evasion rate curve was steeper for those who received the tax-increase questions than that for those who had the tax-decrease questions, as illustrated in **Figure 3.2a**. Also note that the difference in the marginal effects is constant over the range of tax rate in the ME model since it is a linear model (see **Figure 3.2b**). As was already discussed above, these results provide supporting evidence for the ARH.

Figure 3.2: The ME-model-based Evasion Rate Curves and Average Marginal Effects by Tax Increase and Decrease



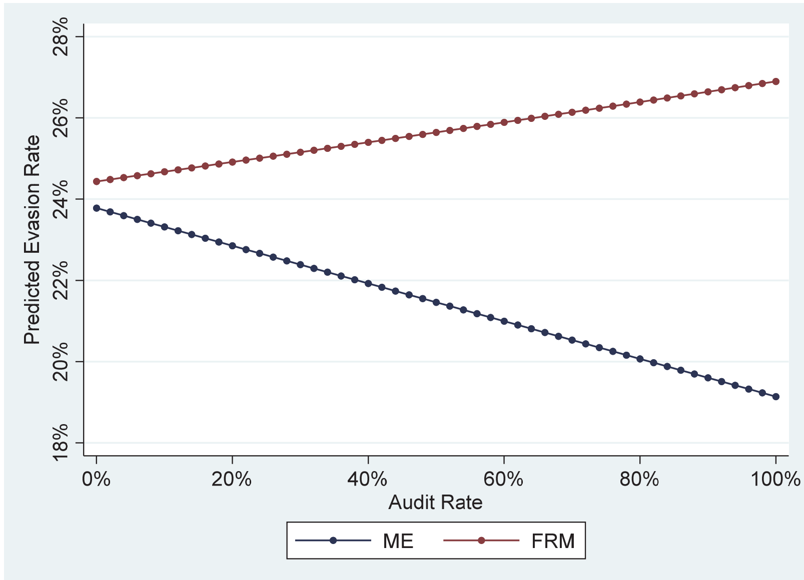
The interaction term was not statistically significant in the FRM, but it was still positive. Again, this positive coefficient implied steeper evasion rate curve for those who received the tax-increase questions (see **Figure 3.3a**). Yet, in case of the FRM, which is a non-linear model, it also means that the difference in the marginal effects between these two groups is widening at the higher values of tax rate, as evident from **Figure 3.3b**.

Figure 3.3: The FRM-based Evasion Rate Curves and Average Marginal Effects by Tax Increase and Decrease



Another key independent variable in the models , at least in theory, is perceived audit rate. In the FRM, the coefficient for this variable was positive, which is contrary to the theory, but it was statistically insignificant. Unlike the FRM, the ME model generated theoretically predicted negative sign for the coefficient. It was also statistically significant in the ME model. However, this estimate was not practically significant by being only -0.046. According to the ME model, *ceteris paribus,* increasing the perceived audit rate from 0% to 100% would reduce the evasion rate by only 4.6 percentage points, as can also be observed in **Figure 3.4**. Thus, this data does not provide strong evidence for a substantial effect of the audit rates on the tax evasion.

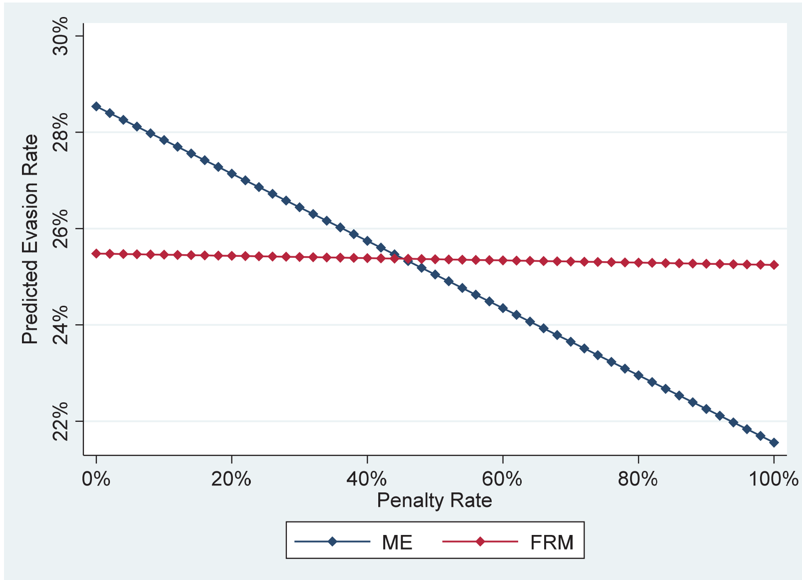
Figure 3.4: Evasion Rate Curves as a Function of Audit Rate
(based on both models)



Weak marginal effect on the evasion rate was observed for perceived penalty rate too. While the coefficient for penalty rate had expected negative sign in both models, it was only statistically significant in the ME model. Moreover, in the FRM, the marginal effect of the penalty was nearly zero, -0.002.[72] Although the ME model yielded the marginal effect larger than the FRM, it was only -0.07. Therefore, as also shown in **Figure 3.5**, increasing the penalty rate from 0% to 100% would reduce the evasion rate by 7 percentage points, holding everything else constant.

Figure 3.5: Evasion Rate Curves as a Function of Penalty Rate
(both models)

[72] Note that the slope of the evasion curve based on the FRM in **Figure 3.4** is almost flat.



Note that the curves produced by the FRM in **Figures 3.3-3.5** are almost linear within the acceptable ranges of tax, audit and penalty rates. Within these ranges, the predicted evasion rate does not reach 0% or 100%. Because of this, the ME model might be better than the FRM in modeling this specific data.[73]

None of the independent variables controlling for personal characteristics were found to be statistically significant in any of the models. The coefficient for the variable *male* was positive, but only significant at 10% level of significance in the ME model. Furthermore, the coefficient was small, which is in line with the findings of Hofmann, Voracek, Bock and Kirchler's (2017) meta-analysis. These researchers also found that "females tend to comply with tax law more than men, but the effect was rather small".

Among the control variables for the social network characteristics only *prop_alterselfemployed* (proportion of alters who are self-employed) was significant in the FRM. Its coefficient had the expected positive sign.

Not surprisingly, those who have been audited had lower evasion rates. The coefficient for *hheveraudited* (whether the respondent or his/her spouse has ever been audited) was negative in both models. However, it was only significant in the FRM. Those who prepared their own taxes seemed to have lower evasion rates. The coefficient for *preptaxesself* was negative in both models too, yet it was significant at only 10% level of significance in the ME model. It should also be noted that the effects of both variables had little practical significance.

Several of the control variables for the respondents' attitudes, beliefs and views were found to be statistically significant. One of them, *prob_deduction* (respondents' subjective probability of them claiming a questionable tax deduction) had a positive coefficient in both models, as expected. The variable also had a relatively large marginal effect. Another significant variable,

[73] It should be emphasized that these curves are fitted lines and all the other control variables are kept at their mean values. Since these are fitted lines, they may not accurately reflect the evasion rates at the extreme points. For example, in **Figure 3.2a** and **3.3a**, the predicted evasion rates are not zero when the tax rate is zero, whereas, by definition, they should be.

actor_more (whether a respondent more likely or somewhat more likely to fully report taxes if a famous actor is known to evade taxes) was also positively correlated with the evasion rate, but its marginal effect was smaller than that of *prob_deduction*.

Beliefs and attitudes toward certain free-riding activities (like avoiding flu vaccination and illegally copying movies) were also found to be associated with the evasion rates. The negative coefficient of *freeriding_never* indicate that people disapproving free-riding activities are likely to have slightly lower evasion rates. Furthermore, *freeriding_percentage* had small, but positive coefficient. This finding suggests that if taxpayers believe that more people are engaged in the free-riding activities, then they would have slightly higher evasion rates. It should be stressed, however, that these effects were quite small.

Interestingly, I did not find any significant association between the evasion rate and respondents' beliefs about worthiness of the public goods and services that they receive. The variable *worthpayingtaxes* (whether a respondent thinks that public goods and services are worth paying taxes for) had insignificant coefficients in both models. Yet, the coefficients had the anticipated negative sign. The coefficient for *importancemoraloblig* (relative importance of *a moral obligation to correctly report and pay taxes* when the respondent thinks about taxes and paying his/her taxes) was also insignificant. This result is in accordance with the findings of the recent study by Jacquemet, Luchini, Malézieux, and Shogren Jason (2019). The authors did not find any significant association between tax compliance and the Moralization of Everyday Life Scale, which is developed by Lovett, Jordan, and Wiltermuth (2012) "to measure variations in people's assignment of moral weight to commonplace behaviors"

The Model-Based Elasticity Estimates

Using the models described in the previous section, I estimated evasion rate elasticities with respect to tax, audit and penalty rates at various points ranging from the 1st percentile to the 99th percentile of the perceived effective tax, audit and penalty rates.[74] Additionally, the elasticities were also estimated at the mean values of the perceived and actual rates. During the estimations, all the other control variables were assumed to be at their mean values.

The elasticities, as well as predicted evasion rates and the marginal effects are presented in **Tables 3.9**, **3.10** and **3.11**. As one can see from these tables, all elasticity estimates were smaller than 1 in absolute values, and they were mostly close to zero. The estimates produced by the ME model were generally higher than those obtained by the FRM. Still, they were less than 1 in magnitude. This suggests that the evasion rates are generally inelastic with respect to tax, audit and penalty rates. Alternatively stated, the taxpayers do not seem to be very responsive to changes in tax, audit and penalty rates.

[74] In case of the perceived penalty rates, the 95th percentile was used instead of the 99th since the latter was an extreme outlier.

The tax elasticity estimates were typically higher than the corresponding estimates obtained for the audit and penalty rates.[75] These estimates varied from 0 to 0.75. The elasticity at the median value of the perceived tax rate was 0.52 in the ME model, and substantially lower, 0.19 in the FRM. Since the median and the mean of the perceived tax rates were close to each other, so were the elasticities valued at these two points, as can be seen in **Table 3.9**.

The tax elasticities could have been even lower, if taxpayers did not tend to overestimate their effective tax rates as was shown in Chapter 2. While average actual effective tax rate is estimated to be 14.3% (own calculations based on the IRS (2017) data), the average perceived effective tax rate is more than 11 percentage points higher. Consequently, the elasticity estimates at the perceived average are higher than those at the actual average (see the table below).

Table 3.9: Tax Elasticity of the Evasion Rate

(Model-Based Estimates)

Estimation Points		Predicted Evasion Rate		Marginal Effect (dydx, in percentage points)		Elasticity (eyex)	
		ME Model	FRM	ME Model	FRM	ME Model	FRM
Baseline Perceived Tax Rates	T = 0.0% (p1)	10.0%	20.0%	0.430	0.157	0.00	0.00
	T = 17.0% (p25)	17.3%	22.9%	0.430	0.177	0.42	0.13
	T = 25.0% (p50)	20.8%	24.3%	0.430	0.186	0.52	0.19
	T = 30.0% (p75)	22.9%	25.3%	0.430	0.192	0.56	0.23
	T = 71.0% (p99)	40.5%	34.2%	0.430	0.243	0.75	0.50
Average Tax Rates	Perceived, T = 25.9%	21.2%	24.5%	0.430	0.187	0.53	0.20
	Actual, T = 14.3%*	16.2%	22.4%	0.430	0.173	0.38	0.11

NOTES: p1, p25, p50, p75 and p99 denote the 1st, 25th, 50th, 75th and 99th percentiles, respectively.

* Own calculations based on the data in Table 1.1 for Tax Year 2015 in Publication 1304, Statistics of Income Division, IRS, September 2017:
https://www.irs.gov/statistics/soi-tax-stats-individual-statistical-tables-by-size-of-adjusted-gross-income#_grp1
[Last accessed on 9/05/2018]

As evident from **Table 3.10**, the audit elasticity estimates cluster around zero. They ranged from 0 to -0.185 when the ME model was used in the calculations. The FRM estimates were positive, but they were nearly zero with the largest estimate being only 0.08. These findings indicate that

[75] This result can be partially because respondents provided more inconsistent responses to the audit and penalty scenario questions than to the tax scenario questions. As was discussed earlier, this difference can partly be due to the way the audit and the penalty questions were asked. The respondents were reminded of their baseline evasion rate just before they received the tax questions, but there were no such reminders for the audit and penalty questions.

the evasion rates are inelastic with respect to the audit rate throughout the entire range of the audit rate.

Table 3.10: Audit Elasticity of the Evasion Rate
(Model-Based Estimates)

Estimation Points		Predicted Evasion Rate		Marginal Effect (dydx, in percentage points)		Elasticity (eyex)	
		ME Model	FRM	ME Model	FRM	ME Model	FRM
Baseline Perceived Audit Rates	A = 0.055% (p1)	23.8%	24.4%	-0.046	0.024	0.000	0.00
	A = 10.0% (p25)	23.3%	24.7%	-0.046	0.024	-0.020	0.01
	A = 20.0% (p50)	22.9%	24.9%	-0.046	0.024	-0.041	0.02
	A = 30.0% (p75)	22.4%	25.2%	-0.046	0.024	-0.062	0.03
	A = 80.0% (p99)	20.1%	26.4%	-0.046	0.025	-0.185	0.08
Average Audit Rates	Perceived, A = 23.6%	22.7%	25.0%	-0.046	0.024	-0.048	0.02
	Actual, A = 0.878%	23.7%	24.5%	-0.046	0.024	-0.002	0.00

NOTE: p1, p25, p50, p75 and p99 denote the 1st, 25th, 50th, 75th and 99th percentiles, respectively.

Like the audit elasticities, the penalty elasticities evaluated at the lower percentiles of the perceived penalty rates were mostly close to zero. Yet, unlike the audit rates the penalty rates were allowed to be greater than 100% in the survey responses. Because of this, higher percentiles of the perceived penalty rates were well above 100%,[76] and the elasticities estimated at these points were closer to 1. Thus, the evasion rates were inelastic over a rather wide interval of the penalty rates, as can be observed from the table below.

Table 3.11: Penalty Elasticity of the Evasion Rate
(Model-Based Estimates)

Estimation Points		Predicted Evasion Rate		Marginal Effect (dydx, in percentage points)		Elasticity (eyex)	
		ME Model	FRM	ME Model	FRM	ME Model	FRM
Baseline Perceived Penalty Rates	P = 0.2% (p1)	28.5%	25.5%	-0.070	-0.002	0.000	0.000
	P = 10.0% (p25)	27.8%	25.5%	-0.070	-0.002	-0.025	-0.001
	P = 20.0% (p50)	27.1%	25.4%	-0.070	-0.002	-0.051	-0.002

76 The maximum value of he perceived penalty rate in the dataset was 1,500%, which was an extreme outlier.

	P = 50.0% (p75)	25.0%	25.4%	-0.070	-0.002	-0.139	-0.005
	P = 200.0% (p95)	14.6%	25.0%	-0.070	-0.002	-0.958	-0.019
Average Penalty Rates	**Perceived, P = 73.5%**	23.4%	25.3%	-0.070	-0.002	-0.219	-0.007
	Actual, P = 75.0%*	23.3%	25.3%	-0.070	-0.002	-0.225	-0.007

NOTES: p1, p25, p50, p75 and p95 denote the 1st, 25th, 50th, 75th and 95th percentiles, respectively.
* The penalty rate for intentionally underreporting taxes can be 75%. Nevertheless, it is rarely enforced since the tax authorities must prove that underreporting is intentional. Typically enforced penalty rate is 20%, which coincides with the median of the perceived penalty rate.

Discussion and Limitations

Key Findings

The analyses in this chapter revealed only weak associations between tax evasion and effective tax, audit and penalty rates. Changes in these rates did not seem to elicit extensive changes in the evasion. The marginal effects and the elasticity estimates were quite small, although they generally had the expected signs. The evasion rates were inelastic (i.e., |eyex| < 1) over the entire possible range of tax and audit rates, and over a large span of penalty rates. Therefore, substantial tax compliance may not be obtained by only using these conventional policy levers.

In part, these relatively small effects of tax, audit and penalty rates on the tax evasion can potentially be explained by lack of understanding. This chapter provides some evidence suggesting that some people may not fully understand the implications of changes in these rates, and hence their behavioral response to these changes may be inconsistent with the standard economic theory. These inconsistent responses seem to lessen the abovementioned effects. Indeed, the estimated effects were stronger when the analyses were re-run without respondents with the inconsistent responses to the tax, audit and penalty questions in the survey.

Structural constraints of the tax system may be another reason for the observed weak effects. For example, a person whose entire income is subject to a third-party reporting may not have an opportunity to cheat. Because of this lack of opportunity, changing audit and penalty rates are not going to impact that person's evasion probability. On the other hand, raising tax rates may encourage the person to look for the sources of income that are hard for tax authorities to detect and measure[77], and consequently, increase the probability. Still, even then such income sources may be limited or altogether unavailable, which in turn will limit the effect of the tax

[77] As an example, the person may seek an employment in the informal sector. Sandmo (2005) extended the A-S model to address this possibility.

rate increase on the evasion rate.

Tax rate also had relatively stronger impact on the evasion than audits and penalties.[78] The estimates of this impact were also generally robust to different model types and specifications considered for this chapter. Yet, this effect varied in magnitude depending on whether the tax rates were increased or decreased. It was larger when the tax rates were increased and smaller when they were reduced. This finding may have an important policy implication. As was argued in Chapter 1, if a government decides to increase the tax rate, then tax compliance may go down. But if later the tax rate is restored to its original value, the pre-change level of tax compliance may not be achieved. Given this potential policy implication, it would be interesting to re-test the ARH in a lab or field experiment, where actual behavior can be observed.

Another hypothesis tested in this chapter was related to tax level relative to expected penalty. Specifically, the analysis did not reveal any significant evidence that taxpayers whose tax rate were larger than their expected penalty were more likely to evade taxes. Additionally, the expected penalty was not found to be significantly associated with the evasion rates.[79] Contrary to the predictions of the standard economic model of tax evasion, these results suggest that taxpayers may not necessarily use expected penalty concept in their decision-making process about tax compliance.

Besides the expected penalty, the evasion rates were also not significantly correlated with most of the considered control variables. Moreover, the significant variables often were significant in one model and not in the other. Some of these insignificant results can potentially be explained by the lack of more detailed information. For example, depending on outcomes and timing of audits, tax compliance may improve or decline in the subsequent periods, as suggested by different empirical studies (Beer, Kasper, Kirchler, & Erard, 2015; Gemmell & Ratto, 2012; Kastlunger, Kirchler, Mittone, & Pitters, 2009; Maciejovsky, Kirchler, & Schwarzenberger, 2007; Mittone, 2006). However, *hheveraudited* variable only had information on whether the respondent or his/her spouse has ever been audited, but no data was available on the outcomes of these audits or when they were conducted. Similarly, *selfemployed* variable indicates only whether a respondent is primarily self-employed or not. Yet, a respondent may have substantial income from side “gigs” like dog-walking, tutoring and driving “Uber”, even when she is not primarily self-employed. If there are many such respondents in the sample, then detecting the impact of self-employment on the evasion rates can be difficult.[80]

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[78] Although it should be mentioned again that this finding can partly be due to fact that the respondents provided more inconsistent responses to the audit and penalty scenario questions than to the tax scenario questions. Relatively weaker effects of the audit and penalty rates can also be explained by the probabilistic nature of these rates. While tax rate changes are usually direct and certain, there is usually some uncertainty if a taxpayer will be audited and if the penalties will be applied. This uncertainty may moderate the effects. (I am grateful to Dr. Kim Bloomquist for this insight.)

[79] Nonetheless, it should be noted that the perceived penalty rates were negatively and significantly related to the evasion rates at least in some of the considered models.

[80] I am thankful to Dr. Kim Bloomquist for pointing out that *selfemployed* variable does not reflect full extent of self-employment income.

Limitations

There are several other important limitations that qualify the findings of this chapter and should be acknowledged. First, the analyses are based on self-reported data, the type of which are known to be vulnerable to numerous problems and biases like comprehension, social desirability bias and memory failures. For example, there is evidence that many audited respondents do not recall being audited (Kasper, Beer, Kirchler, & Erard, 2017). Because of these biases, actual behavior may be different from the reported. Nonetheless, given the results of some studies of self-report and actual behavior in other areas (Clunies-Ross, Little, & Kienhuis, 2008; Huffman, Van Der Werff, Henning, & Watrous-Rodriguez, 2014; Junco, 2013), it may be reasonable to expect that the self-reported behavior is likely to be positively correlated with the actual one in this context too.

Second, the respondents were mostly misinformed about the actual values of effective tax, audit and penalty rates, as was shown in Chapter 2, and they occasionally provided extremely large values for these rates in the baseline scenarios. In the hypothetical scenarios, these values were sometimes further increased making them even more extreme. These outliers, no doubt, influenced the results presented in the chapter. Nevertheless, when these extremely large values were winsorized at 95^{th} percentile, the results were not qualitatively different from those obtained from the original data. After winsorization, the regression coefficients for tax, audit and penalty rates still had the same signs and statistical significance, although their magnitudes slightly changed.

Third, the audit rate questions were asked for all US taxpayers, and not only for a respondent. Specifically, the baseline question was: "*In a typical year, what percent of taxpayers in the US will have their income tax return audited by the IRS?*" A response to this question, while probably being correlated with the subjective probability of the respondent being audited, does not necessarily and always reflect that probability. Therefore, the perceived audit rates were only a proxy for a respondent's perceived probability of being audited.

Finally, as was already discussed above, some respondents, especially those with low numeracy skills, seemed to have difficulty comprehending the hypothetical scenario questions. This incomprehension probably compromised the quality of the data.

To handle this and other problems in the future similar surveys, the questionnaire can be improved in the following ways:

a) The survey respondents can be reminded what their response to the baseline evasion question was right before the audit scenario questions, and then again before the penalty scenario questions.[81] Such reminders can reduce inconsistent answers which are due to lapses of memory.

[81] The tax scenarios questions had this reminder, and there are less inconsistencies in the answers to them.

b) To improve comprehension, the hypothetical scenario questions can be designed in a way that answering them does not require the respondent to calculate the hypothetical rates. Specifically, phrases with percentage changes like "*tax rates are 25% lower than what they currently are*" or "*the audit rate was three times as high as it currently is*" should be avoided in the questions and they should be replaced with specific values instead. As an example, let's consider the following question from the survey: "*Imagine instead that people's effective income tax rates were 25% lower than what they currently are. Out of 100 US taxpayers like you, who continue to work just as many hours, how many do you think would intentionally report less income to the IRS than they actually earned?*". If a respondent's baseline perceived effective tax rate is 20%, then this question can be re-written as: "*Imagine instead that people's effective income tax rates were 15% now (i.e., you pay 15 cents as taxes for every dollar that you earn). Out of 100 US taxpayers like you, who continue to work just as many hours, how many do you think would intentionally report less income to the IRS than they actually earned?*"

c) In the hypothetical scenario questions, the rates can be explained for better understanding. For example, instead of just saying that "*the audit rate was 5 %*", it can be stated as "*the audit rate was 5 % (i.e., out of every 100 taxpayers 5 had their tax returns examined by the IRS)*".

d) For the audit scenario questions, it would be good to also ask questions where the hypothetical audit rates are decreased. The survey questionnaire only had the questions with increased audit rates.

e) It should be stressed and made clear to the respondents that the baseline tax rate question is about federal income taxes. This may reduce any existing confusion whether the question is only about the respondents' federal income tax or their full tax burden.

f) It would also be useful to conduct a cognitive pretest of the questionnaire before fielding the survey. Cognitive pretesting can tell how respondents will interpret the questions and whether these interpretations will be consistent with the research objectives.

Concluding Remarks

The analyses in this chapter confirm that effective tax, audit and penalty rates do matter for tax compliance, but still their effects on the evasion are limited. Effective tax rates seem to have stronger impact on the evasion rates than audit and penalty rates.[82] Moreover, the higher tax rates are associated with the higher evasion rates. This relatively strong positive association and the fact that people tend to overestimate their effective tax rates, as was shown in the previous chapter, creates an opportunity space for behavioral interventions. One of such interventions

[82] However, as was already mentioned, this result can be partly because of the way the data was collected.

will be discussed in the next chapter. A possibility of implementing this intervention will also be examined.

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Chapter 4: Costly Misperceptions: Suggestions for Two Behavioral Interventions to Improve Tax Compliance

Introduction

The purpose of this chapter is to develop two behavioral interventions for tax compliance by applying the findings from the previous chapters. The proposed interventions are simple, relatively minor additions to federal income tax Form 1040. They could substantially reduce tax evasion rates by correcting misperceptions about tax burdens and penalties for underreporting taxes among taxpayers using this form. Thus, if successful, the interventions could potentially increase the amount of income tax paid voluntarily.

This chapter details how these interventions could be implemented. It briefly discusses how and why each of the proposed intervention is expected to work. Additionally, the chapter describes how the key principles of the EAST framework can be applied to the interventions to make them more effective. This framework, described in detail below, was developed by the UK's Behavioral Insights to help policymakers use insights from behavioral science to tackle various policy problems.

The chapter also provides preliminary estimates for the potential impact of the proposed interventions, in terms of: 1) reduction in the evasion rate and 2) additional tax revenues collected due to the interventions. Potential changes in the evasion rates are estimated using a regression model developed in the previous chapter. These estimates are then combined with IRS Tax Gap data to forecast the additional tax revenues that could be recovered by the interventions.

Potential costs of the interventions are highlighted here as well, including both one-time and recurring costs. Approximate numbers are provided for some of these costs.

The final section of the chapter discusses these results and their limitations.

Description of the Interventions

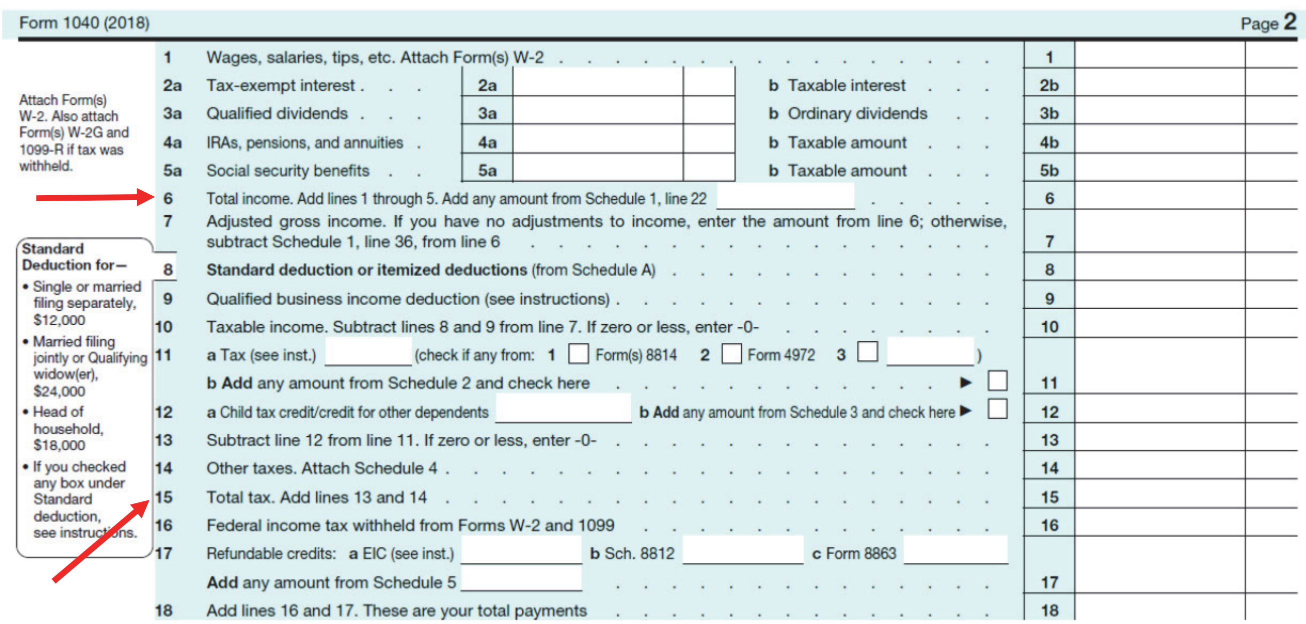
In Chapter 2 it was demonstrated that people have considerable misperceptions about their effective federal income tax rates and the penalties for underreporting taxes. Chapter 3 provided evidence suggesting that these misperceptions may exacerbate tax evasion. Thus, eliminating these misperceptions may prompt people to be more tax compliant. For that purpose, two behavioral interventions are proposed. These two interventions were selected also because they are simple, relatively easy to implement and would require minimum outlay.

The goal of the proposed interventions is to reduce tax evasion by countering misperceptions about effective tax and penalty rates, with the potential to also apply social norms as a motivator. Below is a brief description of both interventions. These interventions are suggestions and can be modified according to the circumstances and the context.

Intervention 1: Correcting Taxpayers Misperceptions About Their Effective Tax Rates

As was shown in the previous chapters, taxpayers tend to overestimate their federal income tax burden, and higher perceived tax rates are associated with higher evasion rates. Therefore, correcting taxpayers' misperceptions about their true effective tax rates may improve tax compliance. This could potentially be accomplished by adding a line for the effective tax rate on the return. This line could be inserted right after line 15, which shows the total tax amount on Form 1040 (see **Figure 4.1** below). In this new line, the effective rate can be calculated by simply dividing the total tax (line 15 in the form) by the total income (line 6 in the form) times 100. An explanatory note can be included stating something like: "Your effective tax rate is ***X***%, which means that you pay ***X*** cents as federal taxes per each dollar that you make." ***X*** in this statement will be the result of the abovementioned calculation.

Figure 4.1: Part of the 2nd Page from Form 1040


Form 1040 (2018) Page 2

Attach Form(s) W-2. Also attach Form(s) W-2G and 1099-R if tax was withheld.

1	Wages, salaries, tips, etc. Attach Form(s) W-2	1
2a	Tax-exempt interest 2a	b Taxable interest 2b
3a	Qualified dividends 3a	b Ordinary dividends 3b
4a	IRAs, pensions, and annuities 4a	b Taxable amount 4b
5a	Social security benefits 5a	b Taxable amount 5b
6	Total income. Add lines 1 through 5. Add any amount from Schedule 1, line 22	6
7	Adjusted gross income. If you have no adjustments to income, enter the amount from line 6; otherwise, subtract Schedule 1, line 36, from line 6	7
8	Standard deduction or itemized deductions (from Schedule A)	8
9	Qualified business income deduction (see instructions)	9
10	Taxable income. Subtract lines 8 and 9 from line 7. If zero or less, enter -0-	10
11	a Tax (see inst.) (check if any from: 1 Form(s) 8814 2 Form 4972 3) b Add any amount from Schedule 2 and check here	11
12	a Child tax credit/credit for other dependents b Add any amount from Schedule 3 and check here	12
13	Subtract line 12 from line 11. If zero or less, enter -0-	13
14	Other taxes. Attach Schedule 4	14
15	Total tax. Add lines 13 and 14	15
16	Federal income tax withheld from Forms W-2 and 1099	16
17	Refundable credits: a EIC (see inst.) b Sch. 8812 c Form 8863 Add any amount from Schedule 5	17
18	Add lines 16 and 17. These are your total payments	18

Standard Deduction for—
• Single or married filing separately, $12,000
• Married filing jointly or Qualifying widow(er), $24,000
• Head of household, $18,000
• If you checked any box under Standard deduction, see instructions.

To make this intervention more effective and efficient, the main principles of the EAST framework can be applied. This framework was developed by the UK's Behavioural Insights Team. Its underlying idea is that "If you want to encourage a behavior, make it Easy, Attractive, Social and Timely (EAST)" (The Behavioural Insights Team, 2014). To *make it easy* for taxpayers, the effective tax rate can be automatically calculated once the total income (line 6) and the total tax (line 15) information are entered in the electronic returns. The automatic calculation will not be possible for the taxpayers who file the paper returns. For these individuals, additional instructions would be required to fill in the new line. This new line could also be optional in the paper form. Making it optional will limit the intervention, but this restriction will be relatively small since only about 10% of the taxpayers file paper returns (IRS, 2018b).

To draw attention to the effective tax rate (*make it attractive*), the new line and the explanatory note accompanying it can be highlighted by using different colors, fonts and designs. As an example, the effective tax rate can be in **bold** fonts and **bright red** or **blue** color.[83] The explanatory note can also be in a different color or put in a text box.

An additional short statement may be added next to the line to emphasize social aspect of taxes (*make it social)*. This statement may be something like "*Most people overestimate their tax rate when in reality it is quite low*." Alternatively, the statement can stress that tax is an important financing mechanism for public goods and services that we all use. Such message may augment the effect of the intervention. For example, a message like "*Paying tax means we all gain from vital public services like the NHS [National Health Service], roads, and schools*" was shown to improve tax compliance in the UK (Hallsworth, List, Metcalfe, & Vlaev, 2017). There is also some experimental evidence suggesting that tax aversion is reduced when taxpayers are reminded about positive uses of taxes they pay (Sussman & Olivola, 2011).

Finally, the effective tax rate should be shown right after the line with the total tax (line 15 in the Form 1040). Such placement will make the rate known to the taxpayers during[84] the filing process, when it is possibly the most relevant to them and while they can still make changes in the return (*make it timely*). Some other times of presenting the effective tax rate can be considered too. For instance, the rate can be stated to the taxpayers after the submittal of the return. It could be either immediately after the submission or before the next filing season. Yet, in these cases, the presented effective tax rate may no longer be relevant to the taxpayer. In particular, the rate from this year may not apply next year due to potential changes in the filing status, the number of dependents and income.

This intervention can reduce tax evasion in at least two ways. First, while filing their returns, tax evaders who overestimate their tax burden will get tax rates that are lower than what they expected. They may perceive these rates to be "suspiciously low", i.e., low enough to attract the tax authorities' attention. To avoid the attention, they may moderate the evasion magnitude to get higher tax rates on their return, or hopefully, may decide against the underreporting of taxes altogether. Thus, the intervention may nudge the evaders to be more compliant.

[83] Kahneman (2011) argues that messages in bold texts and bright red or blue colors are more convincing. He claims that maximizing legibility is likely to make the message more believable.

[84] Although it would be toward the end of the filing process.

Second, the intervention may lessen negative attitudes toward taxes by correcting taxpayers' overestimation of their tax burden. Taxpayers may perceive taxes to be fairer and their willingness to pay taxes may increase. Furthermore, there is some evidence suggesting that people may be willing to accept higher taxes when they are expressed in percent than in dollars (McCaffery & Baron, 2004).[85] Less negative attitudes and higher acceptable tax rates are likely to decrease the probability of a compliant taxpayer becoming an evader. This, in its turn, may lead to improved voluntary compliance in the long term as well. It may also reduce delays in payment of already declared taxes.

Intervention 2: Increasing the Salience of Penalties

As was demonstrated in Chapter 2 (pages 10-13), although there are some who overestimate the statutory penalty rate for any underpayment of tax due to fraud, a great majority underestimate the rate, which is 75% of the underpayment. Correcting this underestimation may improve tax compliance since higher perceived penalty rates are generally associated with lower tax evasion, as was shown in the preceding chapters. To correct the misperceptions, a message about the penalty rate can be included in the tax return form. This message could be as following:

> *"If there is any underpayment on your tax return due to fraud, a penalty of 75% of the underpayment will be added to your tax. You may also be subject to criminal prosecution and imprisonment."*

or

> *"Any underpayment of taxes due to fraud is punishable by an additional penalty of 75% of the underpayment. You may also be subject to criminal prosecution and imprisonment."* [86,87]

The message can be designed to be more compelling by applying the key principles of the EAST framework. Specifically, accessible language should be used to *make the message easy* to read and understand. Different versions of the message can be tested to select the most comprehensible one.

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[85] McCaffery and Baron (2004) asked people what they think fair taxes were for different income levels. The respondents provided higher taxes when they were asked to state the fair taxes in percent than in dollars terms. The authors called this framing effect the *metric effect*. Similar effect was observed in another study by Reimers (2009).

[86] Both versions of the message reflect the language used in "Penalties" section (pages 18-20) in Chapter 1: "Filing Information" of *Publication 17: Tax Guide 2017 for Individuals* (IRS, 2017).

[87] The IRS may audit returns filed within the last six years (IRS, 2019a). Such back audits may increase the amount of penalties imposed, if underreporting is detected in multiple years, although the penalty rate would still be the same. Conveying the information about possible back audits may further improve tax compliance. This can be a separate behavioral intervention.

To highlight the message (*make it attractive*), different format, fonts and colors can be used. For instance, it can be written in **bold red** or **blue** font. Additionally, warning signs can be placed next to the message. Below are the sample messages with the warning signs:

> **If there is any underpayment on your tax return due to fraud, a penalty of 75% of the underpayment will be added to your tax. You may also be subject to criminal prosecution and imprisonment.**

or

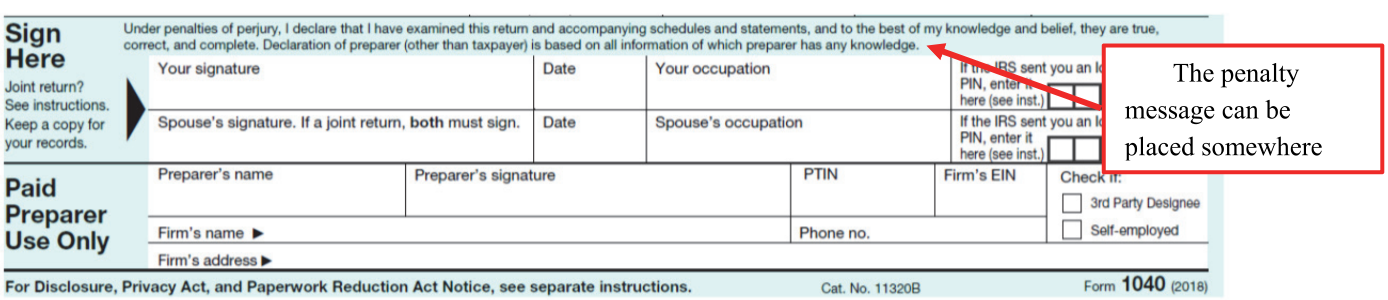
> **WARNING!: If there is any underpayment on your tax return due to fraud, a penalty of 75% of the underpayment will be added to your tax. You may also be subject to criminal prosecution and imprisonment.**

Besides the warning signs, a check-box could also be placed next to the message, and taxpayers could be required to check this box affirming that they read the statements. Several designs can be tested to identify attention-grabbing ones.

This message can be followed by a social norm statement like "*The vast majority of Americans fully pay their federal taxes*" (*make it social*). Similar social norm statements have been successfully utilized to increase tax compliance in Norway and the UK (Bott, Cappelen, Sørensen, & Tungodden, 2017; Hallsworth et al., 2017). However, such statements should be used cautiously since, depending on their wording and the context, they can backfire. There are some field experiments when social norm statements did not work and even slightly worsened tax compliance (Castro & Scartascini, 2015; John & Blume, 2018). Therefore, as with all such interventions, they should be tested before being employed. The same applies to the main message too.

According to the final principle of the EAST framework (*make it timely*), the abovementioned penalty message should be presented to taxpayers when they are most likely to be receptive to it. Ideally, this would be the time immediately before taxpayers decide about tax evasion. Hence it could be a good idea to place the message on the top of the tax return form. To be specific, it can be added above the signature box on the first page of Form 1040, as shown in **Figure 4.2**.

Figure 4.2: Including the Penalty Message on the 1st Page of Form 1040


Sign Here
Under penalties of perjury, I declare that I have examined this return and accompanying schedules and statements, and to the best of my knowledge and belief, they are true, correct, and complete. Declaration of preparer (other than taxpayer) is based on all information of which preparer has any knowledge.
Joint return? See instructions. Keep a copy for your records.
Your signature | Date | Your occupation | If the IRS sent you an Identity Protection PIN, enter it here (see inst.)
Spouse's signature. If a joint return, both must sign. | Date | Spouse's occupation | If the IRS sent you an Identity Protection PIN, enter it here (see inst.)
Paid Preparer Use Only
Preparer's name | Preparer's signature | PTIN | Firm's EIN | Check if: 3rd Party Designee / Self-employed
Firm's name ▶ | Phone no.
Firm's address ▶
For Disclosure, Privacy Act, and Paperwork Reduction Act Notice, see separate instructions. Cat. No. 11320B Form 1040 (2018)

The goal of this proposed intervention is to discourage taxpayers from underreporting their taxes. This goal can be achieved by 1) correcting misperceptions about the penalties that they are low; and 2) increasing the salience of the penalties at the time when taxpayers usually make decision whether to evade taxes or not. Indeed, a similar penalty salience message was found to increase both filing rates and the amount of reported taxes in a controlled field experiment conducted in Detroit, USA (Meiselman, 2018). However, in case of this field experiment, the penalty salience messages were sent after the tax season and not by the time when taxpayers usually make decision about evading taxes. Moreover, the experiment was about city taxes, whereas the proposed intervention is about the federal income tax.

Potential Benefits and Costs of the Interventions

Data and Methods

The fractional response model developed in Chapter 3[88] was used to assess the impact of these interventions on the evasion rate. However, unlike the model in the previous chapter, this time it was estimated with a winsorized[89] dataset. To be precise, the perceived penalty rate variable was winsorized in the ALP Tax Evasion Survey dataset. This variable had few extremely large values. To curtail their effect on the estimates, these outliers were set to the 99th percentile, which was a perceived penalty rate of 400%. Since this transformation only affected 6 observations in the analytic sample, it did not change the model significantly. The model estimated with the winsorized data is presented in **Appendix I**. To compare this model with the one in the previous chapter, please, see **Table 3.8** in Chapter 3.

Besides the ALP Tax Evasion Survey data, IRS data was also used in this chapter. First, the estimates for the actual effective tax rates were calculated based on the data in Table 1.1 in *Publication 1304* by the Statistics of Income Division, IRS. The details of these calculations are described in Chapter 2. The actual effective tax rate estimates were applied in the abovementioned regression models to predict the effect of Intervention 1. Second, to quantify the additional tax revenues that the interventions could potentially generate, the IRS' tax gap data for tax years 2008-2010 were used as well.

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[88] Two models were developed in Chapter 3: a fractional response model and a mixed-effects model. Both models provide qualitatively similar results. Among these two, however, the fractional response model is easier to use for the analysis presented in this chapter. It also yields more conservative estimates than the mixed-effects model.

[89] *Winsorization* is a method of reducing the influence of outliers by usually setting limits to their values. For example, if there is unusually high observation in a dataset, its value can be set to a specified percentile like 95th or 99th percentile.

Potential Benefits of the Interventions

The abovementioned regression model allows prediction of the evasion rate without and with the interventions among those who prepare their tax returns themselves. The model predicted the evasion rate to be 22.22% when there is no intervention, i.e., when the existing perceptions of the penalty and the tax rates stay the same (see **Table 4.1**, which presents the idealized potential effects of the interventions, assuming 100% effectiveness). For Intervention 1 only, the model predicted lower evasion rate of 19.72%. This means that Intervention 1 could potentially reduce the rate by 2.5 percentage points. For Intervention 2 only, the average estimated evasion rate was 22.07%, which is 0.15 percentage points lower than that with no intervention.[90] When both interventions are applied, the predicted potential decrease in the evasion rate is even larger by being 2.65 percentage points.[91]

Table 4.1: Potential Effects of the Two Interventions on the Evasion Rate Among Taxpayers Who Prepare Their Tax Returns Themselves, Assuming 100% Effectiveness in Correcting the Misperceptions

	No intervention	**Intervention 1 only**	**Intervention 2 only**	**Both Interventions**
Predicted Evasion Rates	22.22%	19.72%	22.07%	19.57%
Reduction in Evasion Rates (in percentage points)	--	2.50	0.15	2.65

NOTES: A fractional response model was used to estimate the evasion rates. The regression output for the model is presented in **Table I.1**, **Appendix I**.

Certain assumptions had to be made to estimate the evasion rates with the interventions. First, it was assumed that the interventions would completely eradicate the misperceptions about the tax and penalty rates. This assumption provides a predicted upper bound of the potential effects of the interventions. It should be acknowledged, however, that this assumption may not be realistic and later in the chapter it is relaxed. Second, since the intervention messages would appear on the tax return form, they were assumed to impact only those who prepare their tax returns themselves.[92] This assumption might have biased the evasion-reduction estimates

[90] Note that the estimated impact of Intervention 1 is larger than that of Intervention 2. This is mostly because in the model, the marginal effect of perceived tax rates on perceived tax evasion is larger than that of perceived penalty rates. Similar pattern was observed in some other empirical models of tax evasion (Alm, Jackson, & McKee, 1992; Frey & Feld, 2002; Park & Hyun, 2003; Pommerehne & Weck-Hannemann, 1996).

[91] The mixed-effects model developed in Chapter 3 produced even larger estimates of reduction in the evasion rates. This model predicted the evasion rates to be 19.8% with no intervention, 14.59% with only Intervention 1, 18.03% with only Intervention 2 and 12.82% with both intervention.

[92] About 45% of the respondents in the analytic sample reported that they prepare their own tax returns. This number is little lower than, but not much different from that derived from the IRS data. The IRS estimated that 53.5% used paid practitioner to file their tax returns in tax year 2016 (IRS, 2018a). This means that the remaining 46.5% (=100% - 53.5%) prepared their tax returns themselves.

downward since possible spillover effects, including the effects on paid preparers, were not considered.[93] Nevertheless, given the uncertainties and the current lack of information about these spillover effects, the assumption was not entirely unreasonable to make. Thus, **Table 4.1** should be read with these assumptions in mind.

Both assumptions were reflected in the estimation procedures. For example, to predict the evasion rate for Intervention 1, first, the respondents' perceived effective tax rates were replaced with their actual effective tax rates[94], and all the other characteristics were kept as-is. This replacement was applied only to those who prepare their taxes themselves. Then the fractional response model was used to evaluate the evasion rate at this new set of points. Similarly, for Intervention 2, the same group of the respondents had their perceived penalty rates set to the actual one (i.e., 75%) while everything else stayed the same and then the evasion rate was predicted with the model. The replacements were applied to both the penalty and the tax rates simultaneously when the evasion rate with both interventions was estimated.[95]

An additional assumption was made to express the potential effects of the interventions in monetary terms. Namely, it was presumed that with the interventions, the existing tax gap[96] would decrease proportionally to the reduction in the evasion rate. This assumption allows us to use the following formula to estimate additional revenues that could be collected due to the interventions:

$$R_{int} = G\left(\frac{\hat{E}_{no\ int} - \hat{E}_{int}}{\hat{E}_{no\ int}}\right) f \qquad (4.1)$$

where R_{int} is additional revenue that could be collected due to an intervention, *G* is the tax gap with no intervention and is expressed in dollars, $\hat{E}_{no\ int}$ is the predicted evasion rate with no intervention, $\hat{E}_{int}$ the predicted evasion rate with an intervention, assuming the intervention is 100% effective in correcting the misperceptions; *f* is the effectiveness factor that ranges from 0 to 1 (or 0% to 100%). In this formula, the predicted evasion rates were taken from **Table 4.1**. The current tax gap, *G*, was equated to $113.93 billion per year for those who prepare their tax returns themselves. This number was derived based on the most recent IRS estimate available

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93 For example, people who do not prepare their tax returns may learn about the accurate tax and penalty rates from tax preparers, co-workers, friends and family members. The spillover effect might be especially stronger for the penalties than for the tax rates since the latter is likely to be different for different taxpayers, whereas the former is the same for everyone.

94 The actual effective tax rates were estimated based on the respondents' reported family income brackets. Chapter 2 provides a detailed description of how these estimates were derived.

95 The evasion rates were predicted with the ***margins*** command in STATA. The STATA code for these estimations is available upon request.

96 In this chapter, tax gap is defined as the amount of true tax liability that is not paid voluntarily and on time. This definition is borrowed from *Federal Tax Compliance Research: Tax Gap Estimates for Tax Years 2011-2013* study by the IRS (IRS, 2019b). It is the same as "gross tax gap" concept used in that study.

for the individual income tax gap. According to the IRS, the underreporting tax gap for individual income tax is $245 billion per year (IRS, 2019b).[97] However, this estimate includes underreporting of both those who prepare tax returns themselves and those who use services of tax preparers. Since 46.5%[98] of the taxpayers prepare their taxes themselves, it was assumed that they were responsible for the same portion of the underreporting tax gap or for $113.925 billion (= 46.5%*$245 billion).

Plugging all these numbers into the formula produced the revenue predictions shown in **Table 4.2**. As can be seen in that table, Intervention 1 could generate up to $12.83 billion annually if completely effective. The corresponding number for Intervention 2 is smaller, but it is still substantial at $0.81 billion. If both interventions are implemented, they could potentially yield up to $13.6 billion of additional tax revenues per year (see **Table 4.2**).[99] Even if the effectiveness is substantially lower, the benefits of the interventions could still be sizable, as can be observed from **Table 4.2**.

Table 4.2: Additional Tax Revenues That Could Be Collected Due to the Interventions, Assuming Different Levels of the Intervention Effectiveness (i.e., *f*)

Levels of the Intervention Effectiveness (the effectiveness factor, *f*)	**Additional Tax Revenues** (in billions of dollars)		
	Intervention 1 only	**Intervention 2 only**	**Both Interventions**
100% (*f* = 1)	12.83	0.81	13.60
80% (*f* = 0.8)	10.27	0.65	10.88
60% (*f* = 0.6)	7.70	0.49	8.16
40% (*f* = 0.4)	5.13	0.33	5.44
20% (*f* = 0.2)	2.57	0.16	2.72
10% (*f* = 0.1)	1.28	0.08	1.36

Costs of the Interventions

Obviously, there would be costs associated with the proposed interventions. These costs would be borne by both tax authorities and by taxpayers. Although the costs would be relatively small, some of the larger ones will be briefly discussed in this section.

[97] The IRS defines three tax gap components: 1) non-filing; 2) underreporting and 3) underpayment tax gap (IRS, 2019b). Since the interventions are assumed to impact only those who prepare their tax returns themselves, it is appropriate to use the underreporting tax gap for estimating the potential benefits. It should be noted that the underreporting tax gap number is for tax years 2011-2013 and it is not adjusted for inflation.

[98] This number is estimated based on the IRS data for taxpayers who used paid practitioner to file their tax returns in tax year 2016 (IRS, 2018a). See ***Footnote 92*** for more details.

[99] The additional revenue estimates generated by the mixed-effects model were much bigger. They were $29.99 billion for Intervention 1 only, $10.18 billion for Intervention 2 only and $40.17 billion for both interventions.

There would be one-time costs related to the research and development of the interventions. As an example, at the design stage, the intervention messages described above could be pre-tested in focus-group discussions (or even in qualitative in-depth interviews). Conducting such discussion can cost $8,000 - $10,000 per focus-group. Moreover, it might be required to conduct a randomized field experiment to obtain more reliable estimates for the impact of the interventions. Depending on a scale of the experiment, its cost could range from thousands to a few million dollars. Additionally, adding the intervention messages to the tax return form could entail some editing and computer programming costs of several thousand dollars. Finally, the new tax return form would need to be submitted for OMB Paperwork Reduction Act Review, which would entail administrative costs of producing and reviewing such an application.

Besides the abovementioned one-time costs, the interventions would have recurring ones too. The interventions are likely to increase tax return filing time. This extra time is expected to be negligible per taxpayer given that the proposed return form would only have about three to four additional sentences. Therefore, it is reasonable to assume that it would be no more than three minutes (or 0.05 hours) per return, on average.[100] These three minutes would be worth a little less than $1.40 per return as the current average hourly earnings in the US is slightly less than $28 (Bureau of Labor Statistics, 2019). Therefore, since there were 152.9 million individual income tax returns filed for the last year (IRS, 2019c), the total estimated additional monetized burden would be around $214 million ($1.40 times 152.9 million returns) per year.[101]

To conclude, the costs of the proposed interventions could be sizable. However, they could be substantially outweighed by the potential benefits of the interventions. As was shown in this chapter, even when the proposed interventions are mildly effective, the benefits have the potential to be several times higher than the costs.

Discussion and Limitations

It should be stressed that while the suggested interventions are promising, they would not eradicate a complex and multi-faceted problem like tax evasion completely. They are not silver bullets, but rather low-cost, modest-reward interventions. If we assume that both interventions are 100% effective, affecting everyone and not only those who prepare their tax returns themselves, then the estimated reduction in the evasion rate would be 4.11 percentage points (see **Table J.1** in **Appendix J**). This reduction could potentially help to collect $46.2 billion of additional tax revenues (see **Table J.2** in **Appendix J**), which is a large amount but still a fraction of the individual income tax gap (about 17% of the gross underreporting and non-filing tax gap

[100] For comparison, the IRS estimated that form 1040 for 2018 would take an average of 11.31 hours to complete (U.S. Department of the Treasury, 2018).

[101] These calculations are similar to the ones typically conducted within the Office of Management and Budget reviews.

and over 12% of the total gross tax gap). Nevertheless, given that the estimated benefits are much higher than the estimated costs, it is worth to further explore the possibilities of implementing the interventions. They may prove to be good tools for enhancing tax compliance.

The estimated potential benefits of the interventions increase if more people file their own tax returns. Such expansion could be achieved by making electronic filing systems free and accessible to as many taxpayers as possible, but the analysis here does not explicitly consider the tradeoffs of such a policy. One should expect, however, that the tax preparation industry and some political groups will probably resist the attempts to make these filing systems accessible in the US.[102]

Limitations

The analyses presented in this chapter have certain key limitations. First, the effects of interventions were estimated primarily with self-reported data (i.e., the ALP Tax Evasion Survey). In particular, the respondents' subjective probabilities of tax evasion were used to predict changes in the actual evasion rate. The main assumption here was that when the subjective probabilities decreased due to the corrections made to the perceived tax and penalty rates, so would the tax evasion. Moreover, the actual tax evasion rate was assumed to decline comparably to the reduction in the subjective probabilities. Thus, the accuracy of the potential effect estimates presented in this chapter largely depends on the validity of this assumption. Relaxing this assumption will probably alter the estimates, but the overall conclusions are unlikely to substantially change.

Second, the results also depend on how well the regression model used in this chapter depicts the relationships among the perceived tax rate, the perceived penalty rate and tax evasion. Hence, another key assumption is that this empirical model assesses the effects of these rates on tax evasion reasonably well. This assumption, in its turn, depends on how well the ALP Tax Evasion Survey questions measured the respondents' perceptions about their federal income tax burden and the penalty for underreporting taxes. For example, as was discussed in Chapter 2, the respondents might have overestimated their federal income tax rates because they thought that the survey asked them about their overall taxes and not only federal income tax. This, if true, may weaken the findings of this chapter. It is still reassuring that numerous other empirical studies also found higher tax rates being associated with tax non-compliance (Alm, Deskins, & McKee, 2009; Alm et al., 1992; Clotfelter, 1983; Frey & Feld, 2002; Park & Hyun, 2003; Pommerehne & Frey, 1992; Pommerehne & Weck-Hannemann, 1996).

[102] Interesting discussions of how the tax preparation industry and other political groups make it difficult to expand free electronic filing systems can be found in *Why We Hate Taxes, and Why Some People Want Us To* by Bhanot and Orchinik (2019), *Congress is About to Ban the Government From Offering Free Online Tax Filing. Thank TurboTax* and *TurboTax Deliberately Hid Its Free File Page From Search Engines* by Elliot (Elliott, 2019a, 2019b).

Third, as was already mentioned, it was assumed that the intervention would only impact those who prepare their tax returns themselves, and there would not be any spillover effect. As discussed above, this may not be an entirely realistic assumption. Some taxpayers who have somebody else filing their taxes may still get accurate information about the tax and the penalty rates through tax preparers, friends, colleagues and family members. This chapter (and the dissertation) does not explicitly consider how the information and tax evasion behavior can spread through taxpayers' social network, even though the evasion rate model used to estimate the intervention benefits has certain social network characteristics as control variables.

Fourth, the analyses did not consider potential interaction effects between the proposed interventions. For instance, there might be a synergy between interventions, where their effects amplify each other, or they could weaken each other's impact.

Fifth, the benefit predictions for Intervention 2 only reflect the impact of correcting the misperceptions about the penalty rates. However, salience of the penalties, especially the possibility of criminal prosecution and imprisonment, may influence the outcome as well. Reminding taxpayers about this possibility may further deter some of them from evading taxes. On the other hand, such a reminder may also be perceived as a threat by some taxpayers and may backfire. Furthermore, as was shown in Chapter 2, the perceived penalties were positively correlated with subjective probabilities of tax evasion detection. Consequently, if there is a causal relationship, increasing the salience of the penalties may have additional deterrence effect through the augmented perceptions of detection probabilities. All these possible additional effects of the penalty message have not been considered while estimating the potential impact of Intervention 2.

Finally, this chapter discusses some costs associated with the interventions, but it does not provide the total cost estimates. This is in part because of current uncertainties related to the research and development of the interventions, and will ultimately depend on such considerations as: (a) how many focus groups should be conducted to test the intervention messages, (b) how large should be the sample for the randomized field experiment assessing the impact of the interventions, and (c) should such a sample cover only those who prepare their tax returns themselves or should it also include taxpayers who use services of paid tax preparers? The purpose of this chapter was not to obtain such estimates, but rather to provide a heuristic accounting of potential costs of the interventions under reasonable assumptions. Given the magnitude of the potential gains, these considerations are unlikely to substantively alter the chapter's conclusion that the potential gains greatly outweigh the potential costs.

All these limitations qualify the findings of this chapter. Therefore, as was already mentioned, a randomized field experiment may be required to get more accurate and reliable cost-benefit estimates for the proposed interventions. Focus group studies may also be needed to pre-test the messages of the interventions. Lastly, a study can be conducted to gauge the additional time burden that these interventions would impose on taxpayers. This can be a small-scale randomized control trial or a test that would measure how much time it is required to read the tax return form and the instructions with and without the interventions. Alternatively, the additional time burden can be estimated with IRS Individual Taxpayer Burden Models (ITBM). The models were developed to estimate how changes in the tax forms affect taxpayer burden. For more information about the ITBM see studies by Guyton, O'Hare, Stavrianos, and Toder (2003) and Marcuss et al. (2013)

Concluding Remarks

This dissertation started with a review of the standard economic model for tax evasion. This model, developed by Allingham and Sandmo, allows us to think about a tax evader's decision-making process in a structured way. It is simple, elegant and has capacity for being easily extended to include many real-world complexities. However, it has some major limitations as well. The model mostly focuses on three key policy levers: the probability of detection, penalties and tax rates; and it assumes that taxpayers are well-informed about them.

Chapter 2 showed that this assumption may not be entirely realistic. The empirical analysis presented in that chapter suggests that the US population is largely uninformed about the audit, penalty and tax rates. People mostly overestimate the audit rates and their tax rates. On the other hand, they tend to underestimate penalties. It was also demonstrated that these misperceptions are quite sizable in magnitude.

Chapter 3 explored how the perceptions of tax, audit and penalty rates relate to tax evasion. For that purpose, two econometric models were developed using the ALP Tax Evasion Survey data. These models generally confirmed that perceived penalty rates are negatively correlated with perceived evasion (or, to be exact, with the subjective probability of underreporting taxes). They also provided evidence for positive association between perceived effective tax rates and perceived evasion rate.

The abovementioned findings of Chapter 2 and Chapter 3 underpin the behavioral interventions proposed in the final chapter. The interventions aim to correct taxpayers' misperceptions about their effective tax rate and the penalties for the tax evasion. They consist of simple, relatively minor additions to the federal income tax Form 1040. They are fairly easy and inexpensive to implement. As was shown in Chapter 4, the proposed interventions may potentially help the IRS to collect billions of dollars in additional tax revenues annually.

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APPENDIX A: The American Life Panel Tax Evasion Survey Questionnaire

ALP HOUSEHOLD INFORMATION SECTION

Household information

IF recruitment type = 6 THEN
|
| IF consent form 1 = EMPTY THEN
| | consent1 consent form 1
| | By clicking NEXT below, I certify that I am [name on button] and as of today, am 18 years or older.

| | 1 I understand my participation in the RAND American Life Panel is voluntary and that I can stop participating at any time
| | 2 That is not my name, but I still wish to participate
| | 3 I am not 18 years or older
| |
| | IF consent form 1 = 2 THEN
| | |
| | | consent2 consent form 2
| | | Please enter your name and contact info in this box and we will contact you with correct login information.
| | | Memo
| | ENDIF
| ENDIF
ENDIF
IF (recruitment type = 6 and consent1=1) then) OR recruitment type <> 6 THEN

| IN001 INTRODUCTION

| Our goal is to improve policymaking by informing decision makers about how the public is responding
| to policy changes and life changes. You are part of a randomly selected sample, especially chosen to
| represent the U.S. both geographically and demographically. To make sure that this selection process
| is working properly, we would like you to complete this short questionnaire about your household,
| your background, and your work. By keeping this information current, we will be able to compare our
| panel to U.S. Census data. This will ensure that our results accurately reflect what is happening across
| the nation. We will also be able to assess how different types of households are affected by policy
| changes and life changes. In the future when you login, we will ask you to update us about any
| important changes to your household or your work as described in this questionnaire.

| gender GENDER
| What is your gender?
| 1 Male
| 2 Female

| [Questions IN002 to birthyear are displayed as a table]
| IN002 BIRTH DATE HEADER
| What is your birth date?

| birthmonth BIRTH MONTH
| Month
| from 1- January to 12 - December

| birthday BIRTH DAY
| Day
| from 1 – 01 to 31 – 31
|
| birthyear BIRTH YEAR
| Year
| from 11 – 1911 to 99 - 1999
|
| IF CALCULATED AGE > 100 THEN
| | checkOver100 check age over 100
| | Just to confirm, you are currently [CALCULATED AGE] years old? If not, please go back and fix your birth date. If so, congratulations, and click next!
| ENDIF

| statereside STATE RESIDE
| Now we would like to know about where you live. In which state do you reside?
| 1 (AK) ALASKA (AK)
| 2 (AL) ALABAMA (AL)
| 3 (AZ) ARIZONA (AZ)
| 4 (AR) ARKANSAS (AR)
| 5 (CA) CALIFORNIA (CA)
| 6 (CO) COLORADO (CO)
| 7 (CT) CONNECTICUT (CT)
| 8 (DE) DELAWARE (DE)
| 9 (FL) FLORIDA (FL)
| 10 (GA) GEORGIA (GA)
| 11 (HI) HAWAII (HI)
| 12 (ID) IDAHO (ID)
| 13 (IL) ILLINOIS (IL)
| 14 (IN) INDIANA (IN)
| 15 (IA) IOWA (IA)
| 16 (KS) KANSAS (KS)
| 17 (KY) KENTUCKY (KY)
| 18 (LA) LOUISIANA (LA)
| 19 (ME) MAINE (ME)
| 20 (MD) MARYLAND (MD)
| 21 (MA) MASSACHUSETTS (MA)
| 22 (MI) MICHIGAN (MI)
| 23 (MN) MINNESOTA (MN)

| 24 (MS) MISSISSIPPI (MS)
| 25 (MO) MISSOURI (MO)
| 26 (MT) MONTANA (MT)
| 27 (NE) NEBRASKA (NE)
| 28 (NV) NEVADA (NV)
| 29 (NH) NEW HAMPSHIRE
| 30 (NJ) NEW JERSEY
| 31 (NM) NEW MEXICO
| 32 (NY) NEW YORK
| 33 (NC) NORTH CAROLINA
| 34 (ND) NORTH DAKOTA
| 35 (OH) OHIO (OH)
| 36 (OK) OKLAHOMA (OK)
| 37 (OR) OREGON (OR)
| 38 (PA) PENNSYLVANIA (PA)
| 39 (RI) RHODE ISLAND
| 40 (SC) SOUTH CAROLINA
| 41 (SD) SOUTH DAKOTA
| 42 (TN) TENNESSEE (TN)
| 43 (TX) TEXAS (TX)
| 44 (UT) UTAH (UT)
| 45 (VT) VERMONT (VT)
| 46 (VA) VIRGINIA (VA)
| 47 (WA) WASHINGTON (WA)
| 48 (WV) WEST VIRGINIA
| 49 (WI) WISCONSIN (WI)
| 50 (WY) WYOMING (WY)
| 51 (DC) WASHINGTON D.C. (DC)
| 52 (PR) PUERTO RICO (PR)
|
| borninus BORN IN US
| Were you born in the United States?
| 1 Yes
| 2 No
|
| IF BORN IN US = Yes THEN
| |
| | stateborn STATE BORN
| | In what state were you born?
| | 1 ALASKA (AK)
| | 2 ALABAMA (AL)
| | 3 ARIZONA (AZ)
| | 4 ARKANSAS (AR)
| | 5 CALIFORNIA (CA)
| | 6 COLORADO (CO)
| | 7 CONNECTICUT (CT)
| | 8 DELAWARE (DE)
| | 9 FLORIDA (FL)

| | 10 GEORGIA (GA)
| | 11 HAWAII (HI)
| | 12 IDAHO (ID)
| | 13 ILLINOIS (IL)
| | 14 INDIANA (IN)
| | 15 IOWA (IA)
| | 16 KANSAS (KS)
| | 17 KENTUCKY (KY)
| | 18 LOUISIANA (LA)
| | 19 MAINE (ME)
| | 20 MARYLAND (MD)
| | 21 MASSACHUSETTS (MA)
| | 22 MICHIGAN (MI)
| | 23 MINNESOTA (MN)
| | 24 MISSISSIPPI (MS)
| | 25 MISSOURI (MO)
| | 26 MONTANA (MT)
| | 27 NEBRASKA (NE)
| | 28 NEVADA (NV)
| | 29 NEW HAMPSHIRE (NH)
| | 30 NEW JERSEY (NJ)
| | 31 NEW MEXICO (NM)
| | 32 NEW YORK (NY)
| | 33 NORTH CAROLINA (NC)
| | 34 NORTH DAKOTA (ND)
| | 35 OHIO (OH)
| | 36 OKLAHOMA (OK)
| | 37 OREGON (OR)
| | 38 PENNSYLVANIA (PA)
| | 39 RHODE ISLAND (RI)
| | 40 SOUTH CAROLINA (SC)
| | 41 SOUTH DAKOTA (SD)
| | 42 TENNESSEE (TN)
| | 43 TEXAS (TX)
| | 44 UTAH (UT)
| | 45 VERMONT (VT)
| | 46 VIRGINIA (VA)
| | 47 WASHINGTON (WA)
| | 48 WEST VIRGINIA (WV)
| | 49 WISCONSIN (WI)
| | 50 WYOMING (WY)
| | 51 WASHINGTON D.C.
| | 52 PUERTO RICO
| ENDIF
|
| citizenus CITIZEN US
| Are you a citizen of the United States?
| 1 Yes

| 2 No
|
| currentlivingsituation CURRENT LIVING SITUATION
| Could you tell us what your current living situation is?
| 1 Married or living with a partner
| 2 Separated
| 3 Divorced
| 4 Widowed
| 5 Never married
|
| highesteducation HIGHEST EDUCATION
| What is the highest level of school you have completed or the highest degree you have received?
| 1 Less than 1st grade
| 2 1st,2nd,3rd,or 4th grade
| 3 5th or 6th grade
| 4 7th or 8th grade
| 5 9th grade
| 6 10th grade
| 7 11th grade
| 8 12th grade NO DIPLOMA
| 9 HIGH SCHOOL GRADUATE high school DIPLOMA or the equivalent (For example: GED)
| 10 Some college but no degree
| 11 Associate degree in college Occupational/vocational program
| 12 Associate degree in college Academic program
| 13 Bachelor's degree (For example: BA,AB,BS)
| 14 Master's degree (For example: MA,MS,MEng,MEd,MSW,MBA)
| 15 Professional School Degree (For example: MD,DDS,DVM,LLB,JD)
| 16 Doctorate degree (For example: PhD,EdD)
|
| hispaniclatino HISPANIC LATINO
| Do you consider yourself Hispanic or Latino?
| 1 Yes
| 2 No
|
| IF HISPANIC LATINO = Yes THEN
| |
| | hispaniclatino_detail HISPANIC DETAIL
| | Would you say that you are primarily Mexican American, Puerto Rican, Cuban, or something else?
| | 1 Mexican American
| | 2 Puerto Rican
| | 3 Cuban
| | 4 Something else
| |
| | IF HISPANIC DETAIL = Something else THEN
| | |
| | | hispaniclatino_detail_other HISPANIC DETAIL OTHER
| | | Please specify.
| | | String

| | ENDIF
| ENDIF
|
| white
| Do you consider yourself primarily white or Caucasian, Black or African American, American Indian, or Asian?
| 1 White/Caucasian
| 2 Black/African American
| 3 American Indian or Alaskan Native
| 4 Asian or Pacific Islander
| 5 Other
|
| IF WHITE = Asian or Pacific Islander THEN
| |
| | ethnicity_asianpacificislander ETHNICITY ASIAN OR PACIFIC ISLANDER
| | Are you Asian or Pacific Islander?
| | 1 Asian
| | 2 Pacific Islander
| ENDIF
|
| IF WHITE = Other THEN
| |
| | whiteother WHITE OTHER
| | Please specify.
| | String
| ENDIF
|
| currentjobstatus CURRENT JOB STATUS
| What is your current employment situation?
| 1 Working Now
| 2 Unemployed and looking for work
| 3 Temporarily laid off, on sick or other leave
| 4 Disabled
| 5 Retired
| 6 Homemaker
| 7 Other
|
| IF Other IN CURRENT JOB STATUS THEN
| |
| | currentjobstatusother CURRENT JOB STATUS OTHER
| | Please specify.
| | String
| ENDIF
|
| IF Working Now IN CURRENT JOB STATUS THEN
| |
| | doyouwork DO YOU WORK
| | Next are some questions about your current, main job. Do you work for someone else, are you

| | self-employed, or what?
| | 1 Work for someone else
| | 2 Self-employed
| | 3 Other
| |
| | typework TYPE WORK
| | Which of the following categories best describes the type of work you [DO/DID]?
| | 1 Management Occupations
| | 2 Business and Financial Operations Occupations
| | 3 Computer and Mathematical Occupations
| | 4 Architecture and Engineering Occupations
| | 5 Life, Physical, and Social Science Occupations
| | 6 Community and Social Services Occupations
| | 7 Legal Occupations
| | 8 Education, Training, and Library Occupations
| | 9 Arts, Design, Entertainment, Sports, and Media Occupations
| | 10 Healthcare Practitioner and Technical Occupations
| | 11 Healthcare Support Occupations
| | 12 Protective Service Occupations
| | 13 Food Preparation and Serving Related Occupations
| | 14 Building and Grounds Cleaning and Maintenance Occupations
| | 15 Personal Care and Service Occupations
| | 16 Sales and Related Occupations
| | 17 Office and Administrative Support Occupations
| | 18 Farming, Fishing, and Forestry Occupations
| | 19 Construction and Extraction Occupations
| | 20 Installation, Maintenance, and Repair Occupations
| | 21 Production Occupations
| | 22 Transportation and Material Moving Occupations
| |
| ELSE
| |
| | IF Unemployed and looking for work IN CURRENT JOB STATUS OR Temporarily laid off, on sick or
| | other leave IN CURRENT JOB STATUS OR Disabled IN CURRENT JOB STATUS OR Retired IN CURRENT
JOB
| | STATUS THEN
| | |
| | | typework TYPE WORK
| | | Which of the following categories best describes the type of work you [DO/DID]?
| | | 1 Management Occupations
| | | 2 Business and Financial Operations Occupations
| | | 3 Computer and Mathematical Occupations
| | | 4 Architecture and Engineering Occupations
| | | 5 Life, Physical, and Social Science Occupations
| | | 6 Community and Social Services Occupations
| | | 7 Legal Occupations
| | | 8 Education, Training, and Library Occupations
| | | 9 Arts, Design, Entertainment, Sports, and Media Occupations

| | | 10 Healthcare Practitioner and Technical Occupations
| | | 11 Healthcare Support Occupations
| | | 12 Protective Service Occupations
| | | 13 Food Preparation and Serving Related Occupations
| | | 14 Building and Grounds Cleaning and Maintenance Occupations
| | | 15 Personal Care and Service Occupations
| | | 16 Sales and Related Occupations
| | | 17 Office and Administrative Support Occupations
| | | 18 Farming, Fishing, and Forestry Occupations
| | | 19 Construction and Extraction Occupations
| | | 20 Installation, Maintenance, and Repair Occupations
| | | 21 Production Occupations
| | | 22 Transportation and Material Moving Occupations
| | ENDIF
| ENDIF
|
| householdmembers HOUSEHOLD MEMBERS
| Now we would like to know about other members of your household, if there are any. [/PREVIOUSLY
| YOU INDICATED THAT YOU LIVE WITH YOUR] How many other people live with you [/OTHER THAN
YOUR
| SPOUSE OR PARTNER]? (enter 0 for no one else).
| Range: 0..10
|
| IF HOUSEHOLD MEMBERS > 0 or (HOUSEHOLD MEMBERS = 0 and CURRENT LIVING SITUATION =
Married
| or living with a partner) THEN
| |
| | [Questions IN005 to dummytableend are displayed as a table]
| |
| | IN005 RELATED HEADER
| | Now, please tell us how each person is related to you, as well as indicating the age and gender.
| | [/PLEASE USE THE FIRST LINE FOR YOUR SPOUSE OR PART]
| |
| | householdmember_relation RELATION
| | Relation
| | 1 Spouse/Registered partner (e.g. husband, wife, registered partner)
| | 2 Significant other (e.g. fiancée, boyfriend, girlfriend)
| | 3 Parent (e.g. father, mother, stepfather, stepmother)
| | 4 Child (e.g. son, daughter, stepson, stepdaughter, adopted child)
| | 5 Sibling (e.g. brother, sister, stepbrother, stepsister)
| | 6 Grandparent (e.g. grandfather, grandmother)
| | 7 Grandchild (e.g. grandson, granddaughter)
| | 8 Aunt/uncle
| | 9 Cousin (e.g. nephew, niece, 2d cousin, great nephew)
| | 10 Family-in-law (e.g. father-in-law, sister-in-law)
| | 11 Roommate/housemate (e.g. friend)
| | 12 Financial (e.g. tenant, renter, landlord, employer, nanny)
| | 14 Not related

| | 15 Other
| |
| | relatedage RELATION AGE
| | Age
| | Range: 0..120
| |
| | relatedgender RELATION GENDER
| | Gender
| | 1 Male
| | 2 Female
| |
| | IF HOUSEHOLD MEMBERS > Married or living with a partner or (HOUSEHOLD MEMBERS = Married or
| | living with a partner and CURRENT LIVING SITUATION = Married or living with a partner) THEN
| | |
| | | householdmember_relation RELATION
| | | Relation
| | | 1 Spouse/Registered partner (e.g. husband, wife, registered partner)
| | | 2 Significant other (e.g. fiancée, boyfriend, girlfriend)
| | | 3 Parent (e.g. father, mother, stepfather, stepmother)
| | | 4 Child (e.g. son, daughter, stepson, stepdaughter, adopted child)
| | | 5 Sibling (e.g. brother, sister, stepbrother, stepsister)
| | | 6 Grandparent (e.g. grandfather, grandmother)
| | | 7 Grandchild (e.g. grandson, granddaughter)
| | | 8 Aunt/uncle
| | | 9 Cousin (e.g. nephew, niece, 2d cousin, great nephew)
| | | 10 Family-in-law (e.g. father-in-law, sister-in-law)
| | | 11 Roommate/housemate (e.g. friend)
| | | 12 Financial (e.g. tenant, renter, landlord, employer, nanny)
| | | 14 Not related
| | | 15 Other
| | |
| | | relatedage RELATION AGE
| | | Age
| | | Range: 0..120
| | |
| | | relatedgender RELATION GENDER
| | | Gender
| | | 1 Male
| | | 2 Female
| | ENDIF
| |
| | IF HOUSEHOLD MEMBERS > 5 or (HOUSEHOLD MEMBERS = 5 and CURRENT LIVING SITUATION =
| | Married or iving with a partner) THEN
| | |
| | | householdmember_relation RELATION
| | | Relation
| | | 1 Spouse/Registered partner (e.g. husband, wife, registered partner)
| | | 2 Significant other (e.g. fiancée, boyfriend, girlfriend)

```
| | | 3 Parent (e.g. father, mother, stepfather, stepmother)
| | | 4 Child (e.g. son, daughter, stepson, stepdaughter, adopted child)
| | | 5 Sibling (e.g. brother, sister, stepbrother, stepsister)
| | | 6 Grandparent (e.g. grandfather, grandmother)
| | | 7 Grandchild (e.g. grandson, granddaughter)
| | | 8 Aunt/uncle
| | | 9 Cousin (e.g. nephew, niece, 2d cousin, great nephew)
| | | 10 Family-in-law (e.g. father-in-law, sister-in-law)
| | | 11 Roommate/housemate (e.g. friend)
| | | 12 Financial (e.g. tenant, renter, landlord, employer, nanny)
| | | 14 Not related
| | | 15 Other
| | |
| | | relatedage RELATION AGE
| | | Age
| | | Range: 0..120
| | |
| | | relatedgender RELATION GENDER
| | | Gender
| | | 1 Male
| | | 2 Female
| | ENDIF
| |
| | IF HOUSEHOLD MEMBERS > 5 or (HOUSEHOLD MEMBERS = 5 and CURRENT LIVING SITUATION =
| | Married or iving with a partner) THEN
| | |
| | | householdmember_relation RELATION
| | | Relation
| | | 1 Spouse/Registered partner (e.g. husband, wife, registered partner)
| | | 2 Significant other (e.g. fiancée, boyfriend, girlfriend)
| | | 3 Parent (e.g. father, mother, stepfather, stepmother)
| | | 4 Child (e.g. son, daughter, stepson, stepdaughter, adopted child)
| | | 5 Sibling (e.g. brother, sister, stepbrother, stepsister)
| | | 6 Grandparent (e.g. grandfather, grandmother)
| | | 7 Grandchild (e.g. grandson, granddaughter)
| | | 8 Aunt/uncle
| | | 9 Cousin (e.g. nephew, niece, 2d cousin, great nephew)
| | | 10 Family-in-law (e.g. father-in-law, sister-in-law)
| | | 11 Roommate/housemate (e.g. friend)
| | | 12 Financial (e.g. tenant, renter, landlord, employer, nanny)
| | | 14 Not related
| | | 15 Other
| | |
| | | relatedage RELATION AGE
| | | Age
| | | Range: 0..120
| | |
| | | relatedgender RELATION GENDER
```

| | | Gender
| | | 1 Male
| | | 2 Female
| | ENDIF
| |
| | IF HOUSEHOLD MEMBERS > 5 or (HOUSEHOLD MEMBERS = 5 and CURRENT LIVING SITUATION =
| | Married or iving with a partner) THEN
| | |
| | | householdmember_relation RELATION
| | | Relation
| | | 1 Spouse/Registered partner (e.g. husband, wife, registered partner)
| | | 2 Significant other (e.g. fiancée, boyfriend, girlfriend)
| | | 3 Parent (e.g. father, mother, stepfather, stepmother)
| | | 4 Child (e.g. son, daughter, stepson, stepdaughter, adopted child)
| | | 5 Sibling (e.g. brother, sister, stepbrother, stepsister)
| | | 6 Grandparent (e.g. grandfather, grandmother)
| | | 7 Grandchild (e.g. grandson, granddaughter)
| | | 8 Aunt/uncle
| | | 9 Cousin (e.g. nephew, niece, 2d cousin, great nephew)
| | | 10 Family-in-law (e.g. father-in-law, sister-in-law)
| | | 11 Roommate/housemate (e.g. friend)
| | | 12 Financial (e.g. tenant, renter, landlord, employer, nanny)
| | | 14 Not related
| | | 15 Other
| | |
| | | relatedage RELATION AGE
| | | Age
| | | Range: 0..120
| | |
| | | relatedgender RELATION GENDER
| | | Gender
| | | 1 Male
| | | 2 Female
| | ENDIF
| |
| | IF HOUSEHOLD MEMBERS > 5 or (HOUSEHOLD MEMBERS = 5 and CURRENT LIVING SITUATION =
| | Married or iving with a partner) THEN
| | |
| | | householdmember_relation RELATION
| | | Relation
| | | 1 Spouse/Registered partner (e.g. husband, wife, registered partner)
| | | 2 Significant other (e.g. fiancée, boyfriend, girlfriend)
| | | 3 Parent (e.g. father, mother, stepfather, stepmother)
| | | 4 Child (e.g. son, daughter, stepson, stepdaughter, adopted child)
| | | 5 Sibling (e.g. brother, sister, stepbrother, stepsister)
| | | 6 Grandparent (e.g. grandfather, grandmother)
| | | 7 Grandchild (e.g. grandson, granddaughter)
| | | 8 Aunt/uncle

| | | 9 Cousin (e.g. nephew, niece, 2d cousin, great nephew)
| | | 10 Family-in-law (e.g. father-in-law, sister-in-law)
| | | 11 Roommate/housemate (e.g. friend)
| | | 12 Financial (e.g. tenant, renter, landlord, employer, nanny)
| | | 14 Not related
| | | 15 Other
| | |
| | | relatedage RELATION AGE
| | | Age
| | | Range: 0..120
| | |
| | | relatedgender RELATION GENDER
| | | Gender
| | | 1 Male
| | | 2 Female
| | ENDIF
| |
| | IF HOUSEHOLD MEMBERS > 6 or (HOUSEHOLD MEMBERS = 6 and CURRENT LIVING SITUATION =
| | Married or living with a partner) THEN
| | |
| | | householdmember_relation RELATION
| | | Relation
| | | 1 Spouse/Registered partner (e.g. husband, wife, registered partner)
| | | 2 Significant other (e.g. fiancée, boyfriend, girlfriend)
| | | 3 Parent (e.g. father, mother, stepfather, stepmother)
| | | 4 Child (e.g. son, daughter, stepson, stepdaughter, adopted child)
| | | 5 Sibling (e.g. brother, sister, stepbrother, stepsister)
| | | 6 Grandparent (e.g. grandfather, grandmother)
| | | 7 Grandchild (e.g. grandson, granddaughter)
| | | 8 Aunt/uncle
| | | 9 Cousin (e.g. nephew, niece, 2d cousin, great nephew)
| | | 10 Family-in-law (e.g. father-in-law, sister-in-law)
| | | 11 Roommate/housemate (e.g. friend)
| | | 12 Financial (e.g. tenant, renter, landlord, employer, nanny)
| | | 14 Not related
| | | 15 Other
| | |
| | | relatedage RELATION AGE
| | | Age
| | | Range: 0..120
| | |
| | | relatedgender RELATION GENDER
| | | Gender
| | | 1 Male
| | | 2 Female
| | ENDIF
| |
| | IF HOUSEHOLD MEMBERS > 7 or (HOUSEHOLD MEMBERS = 7 and CURRENT LIVING SITUATION =

| | Married or living with a partner) THEN
| | |
| | | householdmember_relation RELATION
| | | Relation
| | | 1 Spouse/Registered partner (e.g. husband, wife, registered partner)
| | | 2 Significant other (e.g. fiancée, boyfriend, girlfriend)
| | | 3 Parent (e.g. father, mother, stepfather, stepmother)
| | | 4 Child (e.g. son, daughter, stepson, stepdaughter, adopted child)
| | | 5 Sibling (e.g. brother, sister, stepbrother, stepsister)
| | | 6 Grandparent (e.g. grandfather, grandmother)
| | | 7 Grandchild (e.g. grandson, granddaughter)
| | | 8 Aunt/uncle
| | | 9 Cousin (e.g. nephew, niece, 2d cousin, great nephew)
| | | 10 Family-in-law (e.g. father-in-law, sister-in-law)
| | | 11 Roommate/housemate (e.g. friend)
| | | 12 Financial (e.g. tenant, renter, landlord, employer, nanny)
| | | 14 Not related
| | | 15 Other
| | |
| | | relatedage RELATION AGE
| | | Age
| | | Range: 0..120
| | |
| | | relatedgender RELATION GENDER
| | | Gender
| | | 1 Male
| | | 2 Female
| | ENDIF
| |
| | IF HOUSEHOLD MEMBERS > 8 or (HOUSEHOLD MEMBERS = 8 and CURRENT LIVING SITUATION =
| | Married or living with a partner) THEN
| | |
| | | householdmember_relation RELATION
| | | Relation
| | | 1 Spouse/Registered partner (e.g. husband, wife, registered partner)
| | | 2 Significant other (e.g. fiancée, boyfriend, girlfriend)
| | | 3 Parent (e.g. father, mother, stepfather, stepmother)
| | | 4 Child (e.g. son, daughter, stepson, stepdaughter, adopted child)
| | | 5 Sibling (e.g. brother, sister, stepbrother, stepsister)
| | | 6 Grandparent (e.g. grandfather, grandmother)
| | | 7 Grandchild (e.g. grandson, granddaughter)
| | | 8 Aunt/uncle
| | | 9 Cousin (e.g. nephew, niece, 2d cousin, great nephew)
| | | 10 Family-in-law (e.g. father-in-law, sister-in-law)
| | | 11 Roommate/housemate (e.g. friend)
| | | 12 Financial (e.g. tenant, renter, landlord, employer, nanny)
| | | 14 Not related
| | | 15 Other

| | |
| | | relatedage RELATION AGE
| | | Age
| | | Range: 0..120
| | |
| | | relatedgender RELATION GENDER
| | | Gender
| | | 1 Male
| | | 2 Female
| | ENDIF
| |
| | IF HOUSEHOLD MEMBERS > 9 or (HOUSEHOLD MEMBERS = 9 and CURRENT LIVING SITUATION =
| | Married or living with a partner) THEN
| | |
| | | householdmember_relation RELATION
| | | Relation
| | | 1 Spouse/Registered partner (e.g. husband, wife, registered partner)
| | | 2 Significant other (e.g. fiancée, boyfriend, girlfriend)
| | | 3 Parent (e.g. father, mother, stepfather, stepmother)
| | | 4 Child (e.g. son, daughter, stepson, stepdaughter, adopted child)
| | | 5 Sibling (e.g. brother, sister, stepbrother, stepsister)
| | | 6 Grandparent (e.g. grandfather, grandmother)
| | | 7 Grandchild (e.g. grandson, granddaughter)
| | | 8 Aunt/uncle
| | | 9 Cousin (e.g. nephew, niece, 2d cousin, great nephew)
| | | 10 Family-in-law (e.g. father-in-law, sister-in-law)
| | | 11 Roommate/housemate (e.g. friend)
| | | 12 Financial (e.g. tenant, renter, landlord, employer, nanny)
| | | 14 Not related
| | | 15 Other
| | |
| | | relatedage RELATION AGE
| | | Age
| | | Range: 0..120
| | |
| | | relatedgender RELATION GENDER
| | | Gender
| | | 1 Male
| | | 2 Female
| | ENDIF
| ENDIF
|
| familyincome FAMILY INCOME
| Which category represents the total combined income of all members of your family (living here)
| during the past 12 months? This includes money from jobs, net income from business, farm or rent,
| pensions, dividends, interest, social security payments and any other money income received by
| members of your family who are 15 years of age or older.
| 1 Less than $5,000

| 2 $5,000 to $7,499
| 3 $7,500 to $9,999
| 4 $10,000 to $12,499
| 5 $12,500 to $14,999
| 6 $15,000 to $19,999
| 7 $20,000 to $24,999
| 8 $25,000 to $29,999
| 9 $30,000 to $34,999
| 10 $35,000 to $39,999
| 11 $40,000 to $49,999
| 12 $50,000 to $59,999
| 13 $60,000 to $74,999
| 14 $75,000 or more
|
| IF FAMILY INCOME = $75,000 or more THEN
| |
| | familyincome_part2 FAMILY INCOME PART 2
| | You told us that the total combined income of all members of your family (living here) during
| | the preceding 12 months was more than $75,000. Thinking about the total combined income of your
| | family from all sources, approximately how much did members of your family receive during the
| | previous 12 months?
| | 1 $75,000-$99,999
| | 2 $100,000-$124,999
| | 3 $125,000-$199,999
| | 4 $200,000 or more
| ENDIF
|
| internetlocation INTERNET LOCATION
| Finally, we would like to know how you are communicating with us. From what location are you
| currently connected to the Internet?
| 1 Home
| 2 Work
| 3 Internet cafe, library, etc.
| 4 Elsewhere
|
| IF INTERNET LOCATION = Elsewhere THEN
| |
| | internetlocationother INTERNET LOCATION OTHER
| | Please specify.
| | String
| ENDIF
|
| internettypeconnection INTERNET TYPE CONNECTION
| What type of internet connection do you have at that location?
| 1 Dial-up modem (via personal computer or internet player)
| 2 Cable modem
| 3 DSL
| 4 Satellite dish

| 5 Local network
| 6 Other connection
| 7 Don't know
|
| IF INTERNET TYPE CONNECTION = Dial-up modem (via personal computer or internet player) THEN
| |
| | typemodem TYPE MODEM
| | What type of modem do you use to connect to the internet?
| | 1 14.4k modem
| | 2 28.8k modem
| | 3 33.6k modem
| | 4 56k modem
| | 5 Don't know
| ENDIF
|
| email EMAIL
| If you have a new email address, please enter it here. Otherwise, leave this box blank.
| String
ENDIF

MAIN SECTION

Notes to programmers and routing instructions are listed in brackets [] or <> and are not intended to be seen by respondents.

Introductory description (for ALP panelist website)

This survey asks about your experiences and beliefs regarding various taxes and public programs. We are only interested in your perspective – there are no right or wrong answers to any of these questions. As always, your responses will only be used for research purposes, and your individual responses will be confidential.

Random and Preloaded Variables

Create AuditRandom = random[1,2,3].
Create BehavReactionRandom = random[1,2].
Create BehavReactionRandom2 = random[1,2].
Create BehavReactionRandom3 = random[1,2].
Preload CURRENT JOB STATUS and CURRENTLIVINGSITUATION from hhbox.

[Section 1 (Intro)]

<new screen>

This survey asks about your experiences and beliefs regarding various taxes and public programs, and specifically regarding US federal income taxes. We are only interested in your perspective – there are no right or wrong answers to any of these questions. If you are uncertain about the answer to a question, please give your best estimate.

Some of the questions will ask about your perceptions of “people like you.” By this, we mean people you think have similar experiences and perspectives, including things like whether and how much they have worked in the past.

If you file your tax returns jointly with someone else, please respond according to how your income is reported on those tax returns.

As always, your responses will be used only for research purposes, and your individual responses will be confidential.

[Section 2 (Social Network)]

<new screen>

The following questions ask about people you know.

1. [Alters1-10] Please list the initials of 10 adults that you know, other than spouses or domestic partners, and interact with on a regular basis.
    a. [The EgoWeb interface will allow the entry of these ten individuals (alters), and use their initials as the rows in a series of matrix-style questions (a.k.a., stem-and-leaf) as follows in this section. For each of the following questions, the respondent will see the question at the top of the screen, and response rows each labeled with an alter’s initials.]

<new screen>

2. [AlterRel1-10] For each of the people listed below, please indicate your primary relationship with that person.

    [Matrix (stem-and-leaf) with checkboxes for the following columns]

    a. Family member
    b. Friend
    c. Coworker
    d. Other

<new screen>

3. [AlterEduc1-10] For each of the people listed below, please indicate, to the best of your knowledge, what is the highest education degree that person has received?

    [Matrix (stem-and-leaf) with the following columns]

    a. Less than a high school diploma or the equivalent (For example: GED)
    b. High school diploma or the equivalent (For example: GED)
    c. Associate degree in college

d. Bachelor's degree (For example: BA,AB,BS)
e. Graduate degree, such as Master's or Doctoral-level degree

<new screen>

4. [AlterTalkTax1-10] For each of the people listed below, please check the box next to any person with whom you have talked or consulted with about taxes in the past 5 years. This could include any aspect of taxes, including state or federal taxes, tax audits or penalties, how fair taxes seem, or any other related topic.

   [Matrix (stem-and-leaf) with the following columns]

   a. Yes
   b. No
   c. Don't know
   d. I would prefer not to say

<new screen>

5. [For each AlterTalkTax# checked] [AlterHowOften1-10] For these people, how often do you talk to them about taxes?

   [Matrix (stem-and-leaf) with checkboxes for the following columns]

   a. Once every five years
   b. Once every two years
   c. Once a year
   d. Twice a year
   e. Monthly
   f. More frequently
   g. I don't know or don't remember

<new screen>

6. For each of the people below, do you think they are self-employed or have rental income?

   [Matrix (stem-and-leaf) with checkboxes for the following columns]

   a. Yes
   b. No
   c. I don't know or don't remember

<new screen>

7. For each of the people below, do you know or think that they have been audited by the IRS in the past five years?

   [Matrix (stem-and-leaf) with checkboxes for the following columns]

   a. Yes, I know they have been audited
   b. Yes, I think they have been audited
   c. I don't know or don't remember

d. No, I don’t think they have been audited
e. No, I know they have not been audited.

[Section 3 (Audit-rate Perception)]

<new screen>

The following questions ask about your thoughts and experiences regarding US federal income taxes. Specifically, they ask you about three aspects of how income taxes work:

- The <u>audit rate:</u> The percentage of taxpayers whose returns are audited by the IRS,
- The <u>penalty rate:</u> The size of the penalty for not paying all of your owed taxes, and
- The <u>effective income tax rate:</u> The percentage of your income that you owe to the government in taxes.

First let’s consider the <u>audit rate</u>.

8. [PerceivedAuditRate] In a typical year, what percent of taxpayers in the U.S. will have their income tax return audited by the IRS?

   Visual 0-100 subjective probability slider [with checks that response is between 0 and 100]

   a. [If PerceivedAuditRate is less than or equal to 1%] <new screen> [PerceivedAuditRateMagnifier] We would like to get extra information about the last question. In a typical year, what percent of people will have their income tax return audited by the IRS?

      i. 0%
      ii. More than 0% and less than or equal to .001% (1/100,000)
      iii. More than .001% (1/100,000) and less than or equal to .01% (1/10,000)
      iv. More than .01% (1/10,000) and less than or equal to .1% (1/1,000)
      v. More than .1% (1/1,000) and less than or equal to 1% (1/100)
      vi. 1%

<new screen>

9. [PerceivedARUnderreport] Imagine a taxpayer that only paid [30% of the taxes he or she owes, 60% of the taxes he or she owes, 90% of the he or she owes]. Do you think the chances of that person being audited that year would be higher, lower, or the same as if he or she had paid all taxes owed?

   [Programming Note: Randomly assign one of three versions of this question according to RandomAudit, which randomly sets one of three levels of the percentage in the question]

   Higher
   Lower
   The same

a. [IF PerceivedARUnderreport = higher or lower] <new screen> [PerceivedARUProb] What is the percent chance that person will have their income tax return audited by the IRS?

Visual 0-100 subjective probability slider [with checks that response is between 0 and 100]

i. [If PerceivedARUProb is less than or equal to 1%] <new screen> [PerceivedARUMagnifier] We would like to get extra information about the last question. What is the percent chance that person will have their income tax return audited by the IRS?

1. 0%
2. More than 0% and less than or equal to .001% (1/100,000)
3. More than .001% (1/100,000) and less than or equal to .01% (1/10,000)
4. More than .01% (1/10,000) and less than or equal to .1% (1/1,000)
5. More than .1% (1/1,000) and less than or equal to 1% (1/100)
6. 1%

<new screen>

10. [If PerceivedAuditRate is not missing] [BombCrater] If your tax return was audited last year, do you think the chances of being audited the following year are higher, lower, or the same?

Higher
Lower
The same

[Checks: If BombCrater = lower and PerceivedAuditRate = 0%, give error message "The audit rate cannot go lower than 0%." If BombCrater = higher and PerceivedAuditRate = 100%, give error message "The audit rate cannot go higher than 100%."]

a. [If BombCrater = higher or lower] <new screen> [BombCraterAmount] As a reminder, you said earlier that [PerceivedAuditRateMagnifier, or if missing, PerceivedAuditRate] of taxpayers will be audited in a given year. You also said that after an audit the chances of being audited the next year are [BombCrater]. What do you think are these new chances of getting audited?

Visual 0-100 subjective probability slider [with checks that response is between 0 and 100; unlike other slider questions, here please use their response to PerceivedAuditRateMagnifier or, if missing, PerceivedAuditRate as a default value.]

i. [If BombCraterAmount is less than or equal to 1%] <new screen> [BombCraterAmountMagnifier] We would like to get extra information about the last question. What do you think are these new chances of getting audited?

1. 0%
2. More than 0% and less than or equal to .001% (1/100,000)
3. More than .001% (1/100,000) and less than or equal to .01% (1/10,000)

4. More than .01% (1/10,000) and less than or equal to .1% (1/1,000)
5. More than .1% (1/1,000) and less than or equal to 1% (1/100)
6. 1%

[Section 4 (Penalty-rate Perception)]

<new screen>

Now let's consider the <u>penalty rate</u>. If the IRS detects that a person has underreported their taxes, they will first have to pay the unpaid taxes that were due. In addition, they will be assessed a penalty that is a percentage of the amount they underpaid. This percentage is the penalty rate.

11. [PerceivedPenaltyRate] Imagine a person was caught underpaying their taxes by $1000. In addition to having to pay that $1000, how much of a penalty would they have to pay?
    [Response mode: open-response, restricted to non-negative dollar value]

[Section 5 (Tax-rate Perception)]

<new screen>

Now let' consider the <u>effective income tax rate</u>. This is the percent of your income that you owe in taxes to the federal government each year.

12. [PerceivedTaxRate] What do you think your effective income tax rate was this past year?
    Visual 0-100 subjective probability slider [with checks that response is between 0 and 100]

[Section 6 (Tax Evasion Perceptions)]

<new screen>

13. [PerceivedEvasionRatePopulation] In a typical year, out of all taxpayers in the United States, what percent intentionally underreport their taxes?

    Visual 0-100 subjective probability slider [with checks that response is between 0 and 100]

<new screen>

14. [PerceivedEvasionRate] Now consider people like you. In a typical year, out of 100 people like you, how many intentionally underreport their taxes?

    Slider from 0 to 100.

15. [PerceivedEvasionManyEvaders] Imagine that a widely-disseminated news story comes out that half of all US taxpayers underreport their taxes. Out of 100 people like you, how many would now underreport their taxes?

    Slider from 0 to 100.

<new screen>

16. You previously stated that [PerceivedAuditRateMagnifier, or if missing, PerceivedAuditRate] of taxpayers in the U.S. will have their income tax return audited by the IRS. In a typical year, what percent will be caught by the IRS?

    Visual 0-100 subjective probability slider [with checks that response is between 0 and 100; check that less than PerceivedAuditRateMagnifier, or if missing, PerceivedAuditRate, and if not give error "The percent caught should be less than the percent audited."]

[Section 7, Condition A (Perceived Behavioral Reaction to <u>Increased</u> Tax Rate)]

<new screen>

[Programming Note: If the response to PerceievedEvasionRate = 0, then place in Section 7, Condition A. If response to PerceivedEvasionRate = 100, then place in Section 7, Condition B. Otherwise, based on BehavReactionRandom, respondents should either receive the contents of Section 7, Condition A (BehavReactionRandom=1) or Section 7, Condition B (BehavReactionRandom=2).]

[Programming Note: If possible, let's pull these data after about 100 respondents, to make sure that the number of respondents between conditions doesn't get too imbalanced.]

Now let's consider the effect of changing the <u>effective income tax rate</u> (but the audit and penalty rates remain unchanged). As a reminder, you stated earlier that [PerceivedEvasionRate] out of 100 of people like you underreport their taxes to the IRS.

17. [PerceivedUnderreportTaxHigher] Imagine instead that people's effective income tax rates were <u>50% higher</u> than they currently are. Out of 100 US taxpayers <u>like you</u>, who continue to work just as many hours, how many do you think would intentionally underreport their taxes to the IRS?

    Slider from 0 to 100.

18. [PerceivedUnderreportTaxMuchHigher] Imagine instead that people's effective income tax rates were <u>twice as high</u> as they currently are. Out of 100 US taxpayers <u>like you</u>, who continue to work just as many hours, how many do you think would intentionally underreport their taxes to the IRS?

    Slider from 0 to 100.

[Section 7, Condition B (Perceived Behavioral Reaction to <u>Decreased</u> Tax Rate)]

<new screen>

[Programming Note: If the response to PerceievedEvasionRate = 0, then place in Section 7, Condition A. If response to PerceivedEvasionRate = 100, then place in Section 7, Condition B. Otherwise, based on BehavReactionRandom, respondents should either receive the contents of Section 7, Condition A (BehavReactionRandom=1) or Section 7, Condition B (BehavReactionRandom=2).]

[Programming Note: If possible, let's pull these data after about 100 respondents, to make sure that the number of respondents between conditions doesn't get too imbalanced.]

Now let's consider the effect of changing the effective income tax rate (but the audit and penalty rates remain unchanged). As a reminder, you stated earlier that [PerceivedEvasionRate] out of 100 of people like you intentionally report less income to the IRS than they actually earned.

19. [PerceivedUnderreportTaxLower] Imagine instead that people's effective income tax rates were 25% lower than what they currently are. Out of 100 US taxpayers like you, who continue to work just as many hours, how many do you think would intentionally report less income to the IRS than they actually earned?

    Slider from 0 to 100.

20. [PerceivedUnderreportTaxMuchLower] Imagine instead that people's effective income tax rates were half of what they currently are. Out of 100 US taxpayers like you, who continue to work just as many hours, how many do you think would intentionally report less income to the IRS than they actually earned?

    Slider from 0 to 100.

[Section 8 (Perceived Behavioral Reaction to Increased Audit Rate)]

<new screen>

[PROGRAMMING NOTE: Ask questions in this section only if PerceivedEvasionRate > 0]

Now let's consider the effect of changing the audit rate (but the tax and penalty rates remain unchanged).

21. [PerceivedUnderreportAuditHigher] Imagine that the audit rate was twice as high as it currently is. Out of 100 US taxpayers like you, how many do you think would intentionally underreport their taxes to the IRS?

    Slider from 0 to 100.

22. [If PerceivedUnderreportAuditHigher > 0] [PerceivedUnderreportAuditMuchHigher] Imagine that the audit rate was three times as high as it currently is. Out of 100 US taxpayers like you, how many do you think would intentionally underreport their taxes to the IRS?

    Slider from 0 to 100.

[Section 9, Condition A (Perceived Behavioral Reaction to Increased Penalty Rate)]

<new screen>

[Programming Note: If the response to PerceievedEvasionRate = 0, then place in Section 9, Condition B. If response to PerceivedEvasionRate = 100, then place in Section 9, Condition A. Otherwise, based on BehavReactionRandom, respondents should either receive the contents of Section 9, Condition A (BehavReactionRandom=1) or Section 9, Condition B (BehavReactionRandom=2).]

[Programming Note: If possible, let's pull these data after about 100 respondents, to make sure that the number of respondents between conditions doesn't get too imbalanced.]

Now let's consider the effect of changing the penalty rate (but the tax and audit rates remain unchanged). If the federal government detects that you have underreported how much taxes you owe, you will have to pay the unpaid taxes that were due. In addition, you will be assessed a penalty that is a percentage of the amount of taxes due that were unpaid. This percentage is the penalty rate.

23. [PerceivedUnderreportPenaltyHigher] Imagine instead that the penalty rate was 50% higher than it currently is. Out of 100 US taxpayers like you, how many do you think would intentionally underreport their taxes to the IRS?

    Slider from 0 to 100.

24. [IF PerceivedUnderreportPenaltyHigher >0] [PerceivedUnderreportPenaltyMuchHigher] Now imagine that the penalty rate was twice as high as it currently is. Out of 100 US taxpayers like you, how many do you think would intentionally underreport their taxes to the IRS?

    Slider from 0 to 100.

[Section 9, Condition B (Perceived Behavioral Reaction to Decreased Penalty Rate)]

<new screen>

[Programming Note: If the response to PerceievedEvasionRate = 0, then place in Section 9, Condition B. If response to PerceivedEvasionRate = 100, then place in Section 9, Condition A. Otherwise, based on BehavReactionRandom, respondents should either receive the contents of Section 9, Condition A (BehavReactionRandom=1) or Section 9, Condition B (BehavReactionRandom=2).]

[Programming Note: If possible, let's pull these data after about 100 respondents, to make sure that the number of respondents between conditions doesn't get too imbalanced.]

Now let's consider the effect of changing the penalty rate (but the tax and audit rates remain unchanged). If the federal government detects that you have underreported how much taxes you owe, you will have to pay the unpaid taxes that were due. In addition, you will be assessed a penalty that is a percentage of the amount of taxes due that were unpaid. This percentage is the penalty rate.

25. [PerceivedUnderreportPenaltyMuchLower] Imagine instead that the penalty rate was half of what it currently is. Out of 100 US taxpayers like you, how many do you think would intentionally underreport their taxes to the IRS?

Slider from 0 to 100.

26. [IF PerceivedUnderreportPenaltyMuchLower > 0] [PerceivedUnderreportPenaltyLower] Imagine instead that the penalty rate was 25% lower than it currently is. Out of 100 US taxpayers like you, how many do you think would intentionally underreport their taxes to the IRS?

Slider from 0 to 100.

[Section 10 (Perceived Behavioral Reaction to Zero Audit and Penalty Rates)]

<new screen>

[Programming Note: Randomly assign respondents (according to BehavReactionRandom2) to receive either the "people" or "people like you" versions of this question.]

Now finally consider the situation where both audit rate and penalty rate are zero. In this situation no one is audited and hence no one is penalized.

27. [PerceivedUnderreportAuditPenalty] Let's consider how low the effective income tax rate would need to be before everyone reported 100% of their taxes to the IRS, assuming there are no audits or penalties. For this question, assume for the moment that everyone has the same effective tax rate.
    If each of the effective income tax rates below were applied to everyone, please indicate if you think (a) the majority of people like you would report their full income **OR** (b) the majority of people like you would underreport their income.

	Majority of [people/people like you] would report 100% of their taxes	Majority of [people/people like you] would underreport their taxes
Income tax rate = 1%	□	□
Income tax rate = 2.5%	□	□
Income tax rate = 5%	□	□
Income tax rate = 10%	□	□
Income tax rate = 15%	□	□
Income tax rate = 20%	□	□
Income tax rate = 25%	□	□
Income tax rate = 30%	□	□

[Section 11 (Perceived behavioral reaction past refund/tax debt)]

<new screen>

[Programming note: Randomly assign respondents (using BehavReactionRandom3) to either the “receiving a $1000 refund” version of the question (BehavReactionRandom3=1) or the “owing an additional $1000” version of the question (BehavReactionRandom3=2).]

28. Imagine for the moment that last year you [received a $1000 refund/owed an additional $1000] on your federal income taxes. You are now preparing your taxes for this year. You are considering claiming a $1000 deduction, but to the best of your own knowledge you are not entirely sure if it is appropriate for you to take. Without consulting anyone else, what is the percent chance that you will claim this deduction?
    Visual 0-100 subjective probability slider [with checks that response is between 0 and 100]

[Section 12 (Weight of Tax Fairness-related Considerations)]

<new screen>

[Programming note: For this screen, the table should include text boxes in the second column and a counter at the bottom that keeps track of how many tokens they’ve allocated.]

29. For each of the next several sections, we would like to determine how important each of the following issues is to you. For each screen, imagine that you have 100 tokens. Please allocate 100 tokens to the issues below. More tokens means more important.
    In terms of how you think about taxes and paying your taxes, how important is each of the following?

The amount of taxes that I owe (that is, your effective tax rate)	_____
The cost (in time and money) to figure out my taxes	_____
Benefits and public services supported by taxes (for example, public education, security, welfare programs)	_____
A moral obligation to correctly report and pay all my taxes	_____
Total tokens:	[sum counter]

[Section 13 (Weight of personal, network, and media information on fairness)]

<new screen>

[Programming note: For this screen, the table should include text boxes in the second column and a counter at the bottom that keeps track of how many tokens they've allocated.]

30. Now let's consider your thoughts on the <u>fairness of taxes</u>, and what you've seen and heard from those around you. Again, please allocate 100 tokens to the issues below.
    In terms of how fair taxes seem to you, how important is each of the following?

Your own thoughts on the fairness of taxes and the tax system (for example, equity in how different people are taxed and how tax revenue is used by the government)	_____
What you hear and know from friends, family, and other close contacts about the fairness of taxes and the tax system (for example, how often people cheat on their taxes)	_____
What you hear broadly from the media and other sources about the fairness of taxes and the tax system (for example, how often people cheat on their taxes)	_____
Total tokens:	[sum counter]

[Section 14 (Weight of personal, network, and media information on audit/penalty risk)]

<new screen>

[Programming note: For this screen, the table should include text boxes in the second column and a counter at the bottom that keeps track of how many tokens they've allocated.]

31. Now let's consider your thoughts on the <u>risk of audits and penalties</u> for not paying one's taxes. Again, please allocate 100 tokens to the issues below.
    In terms of how you think about these risks, how important is each of the following?

Your own thoughts on the risk of audits and penalties if you don't pay your taxes	_____
What you hear and know from friends, family, and other close contacts about audits and penalties for not paying taxes	_____
What you hear broadly from the media and other sources about audits and penalties for not paying taxes	_____
Total tokens:	[sum counter]

[Section 15 (Perception of services provided by taxes)]

<new screen>

32. Many public goods and services, such as interstate highways, national defense, national parks, and environmental protection, are in part paid for by federal income taxes. To what extent are the public goods and services that you receive worth the federal income taxes you pay?

    1 = Not at all worth it 2 3 4 5 = Definitely worth it

[Section 16 (Free-riding, Part 1)]

<new screen>

Imagine each of the following situations. For each, please indicate if it is always OK to engage in the described behavior, sometimes OK to do it, or never OK to do that behavior.

[Matrix, with responses: Always OK, Sometimes OK, Never OK]

33. [FR11] Regularly listen to public radio without ever contributing.
34. [FR12] Illegally copying, downloading, or streaming movies.
35. [FR13] Have a dog but not getting it spayed or neutered.
36. [FR14] Avoid getting the flu vaccine.
37. [FR15] Avoid paying all of the income tax that you owe.

[Section 17 (Free-riding, Part 2)]

<new screen>

Imagine each of the following situations. For each, how many people out of 100 would say that it is at least sometimes OK to engage in the described behavior.

[Matrix, with responses: 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100]

38. [FR21] Regularly listen to public radio without ever contributing.
39. [FR22] Illegally copying, downloading, or streaming movies.
40. [FR23] Have a dog but not getting it spayed or neutered.
41. [FR24] Avoid getting the flu vaccine.
42. [FR25] Avoid paying all of the income tax that you owe.

[Section 18 (Setting up Future Policy Experiments with ABMs)]

<new screen>

43. [Actor] Imagine that you heard a famous actor was caught and prosecuted for tax evasion. In your mind, would hearing about this make you more or less likely to report all of taxes you owe to the IRS?
    a. I would be much more likely to fully report my income
    b. I would be somewhat more likely to fully report my income
    c. It would not affect my income reporting either way
    d. I would be somewhat less likely to fully report my income
    e. I would be much less likely to fully report my income

[Section 19 (Tax and Audit Experience)]

<new screen>

44. [IF CURRENT JOB STATUS <> working now] [WorkForPay] Have you ever worked for pay?

    Yes
    No

<new screen>

44. [If CURRENT JOB STATUS = working now] [SelfEmployed] Do you work for someone else, are you self-employed, or what?
    Work for someone else
    Self-employed
    Other

<new screen>

44. [EverFiledTaxes] Have you ever filed a tax return yourself or had someone file it for you?
    Yes
    No
    Don't know or can't remember

<new screen>

44. [PrepTaxes] Do you typically prepare your own tax returns or do you pay someone (e.g., an accountant or lawyer) to prepare them for you?
    I prepare my own tax returns using tax software on the computer
    I prepare my own tax returns, without using tax software
    I pay someone else to prepare my tax returns
    I do not prepare a tax return
    I don't know or would prefer not to say

<new screen>

44. [EverAudited] Have you ever been audited by the IRS?
    Yes

No
Don’t know or can’t remember
Prefer not to answer

<new screen>

44. [If CURRENTLIVINGSITUATION = Married or living with a partner] [SpouseAudit] Has your spouse or domestic partner ever been audited by the IRS at any time during the past five years?
    I am not currently married or living with a domestic partner
    Yes
    No
    Don’t know or can’t remember
    Prefer not to answer

APPENDIX B: Partial Reproduction of Table 1.1 from *Statistics of Income -2015: Individual Income Tax Returns (Publication 1304)* and Average Effective Tax Rates by Income

Table 1.1. All Returns: Selected Income and Tax Items, by Size and Accumulated Size of Adjusted Gross Income, Tax Year 2015 (Filing Year 2016)

(All figures are estimates based on samples—money amounts are in thousands of dollars except as indicated)

Size and accumulated size of adjusted gross income	All returns	Taxable returns		Average effective tax rate (based on income tax after credits)*	Average effective tax rate (based on total income tax)*
	Adjusted gross income less deficit	Income tax after credits	Total income tax		
	Amount	Amount	Amount		
	(3)	(14)	(16)	= (14)/(3)	= (16)/(3)
Size of adjusted gross income					
All returns	**10,210,310,102**	**1,435,848,586**	**1,457,891,441**	14.1%	14.3%
No adjusted gross income	-203,775,058	241,975	242,459	-0.1%	-0.1%
$1 under $5,000	26,240,798	40,942	40,941	0.2%	0.2%
$5,000 under $10,000	86,411,986	368,015	368,015	0.4%	0.4%
$10,000 under $15,000	152,752,468	1,381,283	1,381,283	0.9%	0.9%
$15,000 under $20,000	195,857,688	3,523,850	3,523,850	1.8%	1.8%
$20,000 under $25,000	224,230,854	6,191,130	6,191,130	2.8%	2.8%
$25,000 under $30,000	242,572,775	8,752,577	8,752,589	3.6%	3.6%
$30,000 under $40,000	519,525,813	25,167,659	25,167,676	4.8%	4.8%
$40,000 under $50,000	520,845,982	32,530,107	32,530,207	6.2%	6.2%
$50,000 under $75,000	1,228,299,087	99,790,385	99,791,796	8.1%	8.1%
$75,000 under $100,000	1,111,174,843	105,900,927	105,901,459	9.5%	9.5%
$100,000 under $200,000	2,506,497,828	316,328,337	316,349,637	12.6%	12.6%
$200,000 under $500,000	1,546,515,483	297,192,494	299,832,203	19.2%	19.4%
$500,000 under $1,000,000	597,676,645	151,253,134	154,388,762	25.3%	25.8%
$1,000,000 under $1,500,000	236,499,605	64,652,109	66,323,590	27.3%	28.0%
$1,500,000 under $2,000,000	137,686,352	38,594,091	39,671,617	28.0%	28.8%
$2,000,000 under $5,000,000	346,864,436	98,361,813	101,488,542	28.4%	29.3%
$5,000,000 under $10,000,000	195,661,353	54,239,522	56,334,403	27.7%	28.8%
$10,000,000 or more	538,771,167	131,338,237	139,611,281	24.4%	25.9%

Source: IRS, Statistics of Income Division, Publication 1304, September 2017, and own calculations based on this data.
https://www.irs.gov/statistics/soi-tax-stats-individual-statistical-tables-by-size-of-adjusted-gross-income#_grp1

* - Own calculations.

APPENDIX C:

Table C.1: Linear and Fractional Response Models for the Perceived Federal Income Tax Rates

Independent Variables	Correlation Coefficients	Linear Model			GLM, family - binomial, link - log-log				
								Average Marginal Effects	
		Coeff.	S.E.	p-values	Coeff.	S.E.	p-values	dy/dx	S.E.
Personal Characteristic:									
Age	-0.1935	-0.00142	0.0006	0.016	-0.00425	0.0016	0.008	-0.00146	0.0005
Black-African American	0.0286	-0.00598	0.0379	0.875	-0.02032	0.1032	0.844	-0.00695	0.0352
Native American	0.1496	0.18316	0.0749	0.015	0.51606	0.2127	0.015	0.18466	0.0759
Asian	0.0022	-0.01046	0.0330	0.751	-0.03709	0.0920	0.687	-0.01264	0.0311
Other Race	0.0020	-0.06854	0.0358	0.056	-0.20847	0.1007	0.038	-0.06871	0.0316
hispaniclatino	0.1755	0.05228	0.0278	0.060	0.14728	0.0757	0.052	0.05132	0.0267
male	-0.1695	-0.03767	0.0140	0.007	-0.11143	0.0398	0.005	-0.03825	0.0137
married	0.0028	0.02125	0.0163	0.191	0.05672	0.0454	0.211	0.01938	0.0154
education	-0.0554	-0.01479	0.0138	0.285	-0.03474	0.0389	0.372	-0.01189	0.0133
foreignborn	0.0696	0.00961	0.0260	0.712	0.03665	0.0704	0.603	0.01263	0.0244
Estimated Tax Rate	-0.0547	0.23455	0.1650	0.156	0.77258	0.4475	0.084	0.26497	0.1532
selfemployed	-0.0819	-0.03226	0.0156	0.040	-0.09370	0.0464	0.043	-0.03162	0.0154
Social Network Characteristics:									
prop_altersaudited	-0.0039	-0.11294	0.1308	0.388	-0.27146	0.3688	0.462	-0.09310	0.1264
prop_alters_talkTaxes	0.0289	0.01299	0.0262	0.621	0.02607	0.0751	0.728	0.00894	0.0258
prop_alterselfemployed	-0.0008	0.00600	0.0341	0.860	0.02897	0.0932	0.756	0.00994	0.0320
Experiences:									
hheveraudited	0.0444	0.01766	0.0189	0.351	0.04416	0.0499	0.376	0.01523	0.0173
haventfiledtaxes	0.0926	0.02009	0.0507	0.692	0.06841	0.1375	0.619	0.02372	0.0481
preptaxesself	-0.1184	-0.04437	0.0165	0.007	-0.12652	0.0446	0.005	-0.04329	0.0152
Attitudes, beliefs, and views:									
pcaught	0.2290	0.08187	0.0443	0.065	0.24156	0.1245	0.052	0.08285	0.0426
prob_deduction	0.1812	0.06248	0.0231	0.007	0.18073	0.0643	0.005	0.06198	0.0220
actor_more	0.1719	0.00714	0.0202	0.724	0.01663	0.0553	0.764	0.00571	0.0190
freeriding_never	-0.0456	-0.00037	0.0071	0.958	0.00153	0.0194	0.937	0.00053	0.0066
freeriding_percentage	-0.0653	-0.00009	0.0005	0.848	-0.00003	0.0013	0.984	-0.00001	0.0005
worthpayingtaxes	-0.0302	-0.00128	0.0161	0.937	-0.00369	0.0447	0.934	-0.00126	0.0153
importancetaxbenefits	0.0153	0.00024	0.0004	0.575	0.00084	0.0012	0.479	0.00029	0.0004
importancemoraloblig	-0.0689	-0.00035	0.0003	0.274	-0.00116	0.0009	0.185	-0.00040	0.0003
_cons	NA	0.29320	0.0595	0.000	-0.22404	0.1599	0.161	NA	NA
AIC		-1047.3			773.4				
BIC		-918.1			902.7				

APPENDIX D: Evasion Rate Questions from the ALP Tax Evasion Survey

14. [PerceivedEvasionRate] Now consider people like you. In a typical year, out of 100 people like you, how many intentionally underreport their taxes?

Slider from 0 to 100.

[Section 7, Condition A (Perceived Behavioral Reaction to Increased Tax Rate)]

<new screen>
[Programming Note: If the response to PerceievedEvasionRate = 0, then place in Section 7, Condition A. If response to PerceivedEvasionRate = 100, then place in Section 7, Condition B. Otherwise, based on BehavReactionRandom, respondents should either receive the contents of Section 7, Condition A (BehavReactionRandom=1) or Section 7, Condition B (BehavReactionRandom=2).]

[Programming Note: If possible, let's pull these data after about 100 respondents, to make sure that the number of respondents between conditions doesn't get too imbalanced.]

Now let's consider the effect of changing the effective income tax rate (but the audit and penalty rates remain unchanged). As a reminder, you stated earlier that [PerceivedEvasionRate] out of 100 of people like you underreport their taxes to the IRS.

17. [PerceivedUnderreportTaxHigher] Imagine instead that people's effective income tax rates were 50% higher than they currently are. Out of 100 US taxpayers like you, who continue to work just as many hours, how many do you think would intentionally underreport their taxes to the IRS?

Slider from 0 to 100.

18. [PerceivedUnderreportTaxMuchHigher] Imagine instead that people's effective income tax rates were twice as high as they currently are. Out of 100 US taxpayers like you, who continue to work just as many hours, how many do you think would intentionally underreport their taxes to the IRS?

Slider from 0 to 100.

[Section 7, Condition B (Perceived Behavioral Reaction to Decreased Tax Rate)]

<new screen>
[Programming Note: If the response to PerceievedEvasionRate = 0, then place in Section 7, Condition A. If response to PerceivedEvasionRate = 100, then place in Section 7, Condition B. Otherwise, based on BehavReactionRandom, respondents should either receive the contents of Section 7, Condition A (BehavReactionRandom=1) or Section 7, Condition B (BehavReactionRandom=2).]

[Programming Note: If possible, let's pull these data after about 100 respondents, to make sure that the number of respondents between conditions doesn't get too imbalanced.]

Now let's consider the effect of changing the effective income tax rate (but the audit and penalty rates remain unchanged). As a reminder, you stated earlier that [PerceivedEvasionRate] out of 100 of people like you intentionally report less income to the IRS than they actually earned.

19. [PerceivedUnderreportTaxLower] Imagine instead that people's effective income tax rates were 25% lower than what they currently are. Out of 100 US taxpayers like you, who continue to work just as many hours, how many do you think would intentionally report less income to the IRS than they actually earned?

Slider from 0 to 100.

20. [PerceivedUnderreportTaxMuchLower] Imagine instead that people's effective income tax rates were half of what they currently are. Out of 100 US taxpayers like you, who continue to work just as many hours, how many do you think would intentionally report less income to the IRS than they actually earned?

Slider from 0 to 100.

[Section 8 (Perceived Behavioral Reaction to Increased Audit Rate)]

<new screen>
[PROGRAMMING NOTE: Ask questions in this section only if PerceivedEvasionRate > 0]

Now let's consider the effect of changing the audit rate (but the tax and penalty rates remain unchanged).

21. [PerceivedUnderreportAuditHigher] Imagine that the audit rate was twice as high as it currently is. Out of 100 US taxpayers like you, how many do you think would intentionally underreport their taxes to the IRS?

Slider from 0 to 100.

22. [If PerceivedUnderreportAuditHigher > 0] [PerceivedUnderreportAuditMuchHigher] Imagine that the audit rate was three times as high as it currently is. Out of 100 US taxpayers like you, how many do you think would intentionally underreport their taxes to the IRS?

Slider from 0 to 100.

[Section 9, Condition A (Perceived Behavioral Reaction to Increased Penalty Rate)]

<new screen>
[Programming Note: If the response to PerceievedEvasionRate = 0, then place in Section 9, Condition B. If response to PerceivedEvasionRate = 100, then place in Section 9, Condition A. Otherwise, based on BehavReactionRandom, respondents should either receive the contents of Section 9, Condition A (BehavReactionRandom=1) or Section 9, Condition B (BehavReactionRandom=2).]
[Programming Note: If possible, let's pull these data after about 100 respondents, to make sure that the number of respondents between conditions doesn't get too imbalanced.]

Now let's consider the effect of changing the <u>penalty rate</u> (but the tax and audit rates remain unchanged). If the federal government detects that you have underreported how much taxes you owe, you will have to pay the unpaid taxes that were due. In addition, you will be assessed a penalty that is a percentage of the amount of taxes due that were unpaid. This percentage is the penalty rate.

23. [PerceivedUnderreportPenaltyHigher] Imagine instead that the penalty rate was <u>50% higher</u> than it currently is. Out of 100 US taxpayers <u>like you</u>, how many do you think would intentionally underreport their taxes to the IRS?

Slider from 0 to 100.

24. [IF PerceivedUnderreportPenaltyHigher >0] [PerceivedUnderreportPenaltyMuchHigher] Now imagine that the penalty rate was <u>twice as high</u> as it currently is. Out of 100 US taxpayers <u>like you</u>, how many do you think would intentionally underreport their taxes to the IRS?

Slider from 0 to 100.

[Section 9, Condition B (Perceived Behavioral Reaction to Decreased Penalty Rate)]

<new screen>
[Programming Note: If the response to PerceievedEvasionRate = 0, then place in Section 9, Condition B. If response to PerceivedEvasionRate = 100, then place in Section 9, Condition A. Otherwise, based on BehavReactionRandom, respondents should either receive the contents of Section 9, Condition A (BehavReactionRandom=1) or Section 9, Condition B (BehavReactionRandom=2).]
[Programming Note: If possible, let's pull these data after about 100 respondents, to make sure that the number of respondents between conditions doesn't get too imbalanced.]

Now let's consider the effect of changing the <u>penalty rate</u> (but the tax and audit rates remain unchanged). If the federal government detects that you have underreported how much taxes you owe, you will have to pay the unpaid taxes that were due. In addition, you will be assessed a penalty that is a percentage of the amount of taxes due that were unpaid. This percentage is the penalty rate.

25. [PerceivedUnderreportPenaltyMuchLower] Imagine instead that the penalty rate was <u>half</u> of what it currently is. Out of 100 US taxpayers <u>like you</u>, how many do you think would intentionally underreport their taxes to the IRS?

Slider from 0 to 100.

26. [IF PerceivedUnderreportPenaltyMuchLower > 0] [PerceivedUnderreportPenaltyLower] Imagine instead that the penalty rate was <u>25% lower</u> than it currently is. Out of 100 US taxpayers <u>like you</u>, how many do you think would intentionally underreport their taxes to the IRS?

Slider from 0 to 100.

APPENDIX E: Regression Output for the Models Used in the ARH Testing

Table E.1: Mixed-Effects Model with an Interaction Term Between the Random Assignment* and Tax Rate

Independent Variables	**Coefficients**	**S.E.**	**p-values**	**95% Conf. Interval**	
Perceived Rates, the Group Assignment and the Interaction Term:					
Tax rate	0.308	0.0619	<0.001	0.187	0.429
randomtaxincrease	-0.022	0.0223	0.325	-0.066	0.022
randomtaxincrease*Tax rate	0.230	0.0769	0.003	0.080	0.381
Audit rate	-0.046	0.0232	0.045	-0.092	-0.001
Penalty rate	-0.070	0.0237	0.003	-0.116	-0.023
Personal Characteristic:					
Age	-0.001	0.0006	0.341	-0.002	0.001
Black-African American	0.011	0.0258	0.662	-0.039	0.062
Native American	0.087	0.0664	0.191	-0.043	0.217
Asian	-0.057	0.0456	0.210	-0.146	0.032
Other Race	0.033	0.0391	0.399	-0.044	0.110
hispaniclatino	0.002	0.0261	0.938	-0.049	0.053
male	0.028	0.0151	0.069	-0.002	0.057
married	-0.024	0.0164	0.147	-0.056	0.008
education	-0.013	0.0159	0.418	-0.044	0.018
foreignborn	0.020	0.0279	0.472	-0.035	0.075
Marginal Tax Rate	-0.136	0.1092	0.214	-0.350	0.078
self-employed	0.011	0.0198	0.576	-0.028	0.050
Social Network Characteristics:					
prop_altersaudited	0.049	0.1268	0.698	-0.199	0.298
prop_alters_talkTaxes	-0.028	0.0263	0.294	-0.079	0.024
prop_alterselfemployed	0.025	0.0375	0.502	-0.048	0.099
Experiences:					
hheveraudited	-0.024	0.0183	0.182	-0.060	0.011
haventfiledtaxes	0.079	0.0544	0.148	-0.028	0.185
preptaxesself	-0.029	0.0153	0.058	-0.059	0.001
Attitudes, beliefs, and views:					
prob_deduction	0.105	0.0253	<0.001	0.056	0.155
actor_more	0.034	0.0185	0.064	-0.002	0.070
freeriding_never	-0.014	0.0070	0.048	-0.027	0.000
freeriding_percentage	0.001	0.0004	0.084	0.000	0.002
worthpayingtaxes	-0.008	0.0151	0.594	-0.038	0.022
importancetaxbenefits	0.000	0.0004	0.923	-0.001	0.001
importancemoraloblig	0.000	0.0003	0.273	-0.001	0.000
constant	0.215	0.0556	<0.001	0.106	0.324
Number of observations = 5,159			Wald chi2(30) = 285.08		

Number of groups (respondents) = 752	p-value < 0.001

NOTE: * - The variable for the random assignment is *randomtaxincrease*, which is equal to 1 if a respondent was randomly assigned the tax-increase questions and 0 if he/she randomly received the tax-decrease questions. All respondents with non-random assignments to these two groups were excluded from the analysis.

Table E.2: Fractional Response Model with an Interaction Term Between the Random Assignment[1)] and Tax Rate (GEE estimation method)

Independent Variables	Coefficients	Average Marginal Effects (dydx)	S.E. for dydx	p-values for dydx	95% Conf. Interval for dydx	
Perceived Rates, the Group Assignment and the Interaction Term:						
Tax rate	0.665	0.134[2)]	0.0644	0.037	0.008	0.260
randomtaxincrease	0.028	0.033	0.0176	0.060	-0.001	0.068
randomtaxincrease*Tax rate	0.432	0.106	--	0.189	--	--
Audit rate	0.115	0.024	0.0348	0.485	-0.044	0.093
Penalty rate	-0.011	-0.002	0.0020	0.234	-0.006	0.002
Personal Characteristic:						
Age	0.000	0.000	0.0006	0.948	-0.001	0.001
Black-African American	-0.046	-0.010	0.0278	0.730	-0.064	0.045
Asian	-0.424	-0.078	0.0365	0.032	-0.150	-0.007
Other Race	0.244	0.055	0.0411	0.183	-0.026	0.135
hispaniclatino	-0.080	-0.017	0.0280	0.554	-0.071	0.038
male	0.030	0.006	0.0193	0.742	-0.032	0.044
married	0.019	0.004	0.0216	0.857	-0.038	0.046
education	-0.021	-0.004	0.0228	0.847	-0.049	0.040
foreignborn	0.200	0.044	0.0351	0.210	-0.025	0.113
Marginal Tax Rate	-0.716	-0.151	0.1311	0.250	-0.408	0.106
self-employed	0.012	0.003	0.0333	0.939	-0.063	0.068
Social Network Characteristics:						
prop_altersaudited	0.698	0.147	0.0931	0.115	-0.036	0.330
prop_alters_talkTaxes	-0.241	-0.051	0.0357	0.155	-0.121	0.019
prop_alterselfemployed	0.463	0.097	0.0396	0.014	0.020	0.175
Experiences:						
hheveraudited	-0.260	-0.052	0.0227	0.022	-0.096	-0.007
haventfiledtaxes	0.006	0.001	0.0360	0.973	-0.069	0.072
preptaxesself	-0.118	-0.025	0.0203	0.223	-0.065	0.015
Attitudes, beliefs, and views:						
prob_deduction	0.605	0.127	0.0274	0.000	0.074	0.181
actor_more	0.225	0.049	0.0256	0.056	-0.001	0.099
freeriding_never	-0.053	-0.011	0.0074	0.133	-0.026	0.003
freeriding_percentage	0.006	0.001	0.0005	0.005	0.000	0.002
worthpayingtaxes	-0.114	-0.024	0.0194	0.215	-0.062	0.014
importancetaxbenefits	0.003	0.001	0.0004	0.193	0.000	0.001
importancemoraloblig	0.000	0.000	0.0004	0.963	-0.001	0.001

constant	-1.894	--	--	--	--	--
Number of observations = 5,084			Wald chi2(29) = 210.44			
Number of groups (respondents) = 741			p-value < 0.001			

NOTE: 1) - The variable for the random assignment is *randomtaxincrease*, which is equal to 1 if a respondent was randomly assigned the tax-increase questions and 0 if he/she randomly received the tax-decrease questions. All respondents with non-random assignments to these two groups were excluded from the analysis.

2) – For the sake of comparison with the ME model, the reported average marginal effect for tax rate is for when the tax rate is decreased. The overall average marginal effect for the tax rate was 0.191 with SE = 0.043. P-value for the interaction term is a p-value for the test between the differences in the average marginal effects for the cases when the tax rates are increased and decreased

3) - The binary variable for Native Americans were dropped out of the analysis because of collinearity.

APPENDIX F: Regression Models of the Evasion Rate with the Expected Penalty Rate as an Independent Variable

Table F.1: Mixed-Effects Model of the Evasion Rate with the Expected Penalty Rate

Independent Variables	Coefficients	S.E.	p-values	95% Conf. Interval	
Perceived Rates, the Assignment of Tax-Increase or -Decrease Questions:					
Tax rate	0.312	0.0613	<0.001	0.192	0.432
randomtaxincrease	-0.027	0.0221	0.229	-0.070	0.017
randomtaxincrease*Tax rate	0.240	0.0769	0.002	0.089	0.390
Audit rate	-0.044	0.0233	0.060	-0.089	0.002
Expected Penalty rate	-0.130	0.0948	0.172	-0.315	0.056
Personal Characteristic:					
Age	-0.001	0.0006	0.187	-0.002	0.000
Black-African American	0.006	0.0252	0.825	-0.044	0.055
Native American	0.082	0.0795	0.302	-0.074	0.238
Asian	-0.061	0.0441	0.163	-0.148	0.025
Other Race	0.035	0.0402	0.382	-0.044	0.114
hispaniclatino	0.004	0.0268	0.869	-0.048	0.057
male	0.029	0.0149	0.051	0.000	0.058
married	-0.026	0.0163	0.112	-0.058	0.006
education	-0.016	0.0159	0.323	-0.047	0.015
foreignborn	0.018	0.0279	0.522	-0.037	0.073
Marginal Tax Rate	-0.153	0.1075	0.155	-0.363	0.058
self-employed	0.007	0.0197	0.725	-0.032	0.046
Social Network Characteristics:					
prop_altersaudited	0.036	0.1326	0.787	-0.224	0.296
prop_alters_talkTaxes	-0.025	0.0262	0.333	-0.077	0.026
prop_alterselfemployed	0.041	0.0378	0.274	-0.033	0.115
Experiences:					
hheveraudited	-0.022	0.0186	0.247	-0.058	0.015
haventfiledtaxes	0.074	0.0557	0.185	-0.035	0.183
preptaxesself	-0.028	0.0150	0.058	-0.058	0.001
Attitudes, beliefs, and views:					
prob_deduction	0.105	0.0247	<0.001	0.056	0.153
actor_more	0.032	0.0183	0.086	-0.004	0.067
freeriding_never	-0.013	0.0070	0.055	-0.027	0.000
freeriding_percentage	0.001	0.0004	0.039	0.000	0.002
worthpayingtaxes	-0.008	0.0150	0.594	-0.037	0.021
importancetaxbenefits	0.000	0.0004	0.992	-0.001	0.001
importancemoraloblig	0.000	0.0003	0.393	-0.001	0.000
constant	0.209	0.0548	<0.001	0.102	0.317
Number of observations = 5,152			Wald chi2(30) = 279.27		

Number of groups (respondents) = 751	p-value < 0.001

Table F.2: Fractional Response Model of the Evasion Rate with the Expected Penalty Rate

Independent Variables	Coefficients	Average Marginal Effects (dydx)	S.E. for dydx	p-values for dydx	95% Conf. Interval for dydx	
Perceived Rates, the Group Assignment and the Interaction Term:						
Tax rate	0.667	0.191	0.0430	<0.001	0.107	0.275
randomtaxincrease	0.027	0.033	0.0177	0.061	-0.001	0.068
randomtaxincrease*Tax rate	0.433	--	--	--	--	--
Audit rate	0.116	0.024	0.0349	0.485	-0.044	0.093
Expected Penalty rate	-0.015	-0.003	0.0030	0.309	-0.009	0.003
Personal Characteristic:						
Age	0.000	0.000	0.0006	0.934	-0.001	0.001
Black-African American	-0.047	-0.010	0.0279	0.727	-0.064	0.045
Asian	-0.419	-0.077	0.0365	0.034	-0.149	-0.006
Other Race	0.246	0.055	0.0411	0.179	-0.025	0.136
hispaniclatino	-0.080	-0.017	0.0279	0.554	-0.071	0.038
male	0.029	0.006	0.0193	0.751	-0.032	0.044
married	0.019	0.004	0.0216	0.855	-0.038	0.046
education	-0.020	-0.004	0.0228	0.852	-0.049	0.040
foreignborn	0.196	0.043	0.0351	0.219	-0.026	0.112
Marginal Tax Rate	-0.713	-0.150	0.1310	0.252	-0.407	0.107
self-employed	0.014	0.003	0.0333	0.929	-0.062	0.068
Social Network Characteristics:						
prop_altersaudited	0.701	0.148	0.0930	0.112	-0.035	0.330
prop_alters_talkTaxes	-0.245	-0.052	0.0357	0.148	-0.122	0.018
prop_alterselfemployed	0.465	0.098	0.0395	0.013	0.021	0.175
Experiences:						
hheveraudited	-0.259	-0.052	0.0226	0.023	-0.096	-0.007
haventfiledtaxes	0.007	0.001	0.0365	0.968	-0.070	0.073
preptaxesself	-0.118	-0.025	0.0203	0.220	-0.065	0.015
Attitudes, beliefs, and views:						
prob_deduction	0.606	0.128	0.0274	<0.001	0.074	0.181
actor_more	0.226	0.049	0.0256	0.055	-0.001	0.099
freeriding_never	-0.052	-0.011	0.0074	0.139	-0.025	0.004
freeriding_percentage	0.006	0.001	0.0005	0.005	0.000	0.002
worthpayingtaxes	-0.114	-0.024	0.0194	0.216	-0.062	0.014
importancetaxbenefits	0.003	0.001	0.0004	0.196	0.000	0.001
importancemoraloblig	0.000	0.000	0.0004	0.955	-0.001	0.001
constant	-1.899	--	--	--	--	--
Number of observations = 5,077			Wald chi2(29) = 207.35			
Number of groups (respondents) = 740			p-value < 0.001			

APPENDIX G: List of Covariates Used in the Regression Analysis and Their Descriptive Statistics

Covariates	Measurement units	Mean or %*	SD	Min	Q1	Median	Q3	Max	Missing, including legal skips (n)
Perceived Rates and the Group Assignment:									
Tax rate	fraction	0.239	0.143	0	0.15	0.25	0.3	1	29
randomtaxincrease	percent	42.08%	--	--	--	--	--	--	151
Audit rate	fraction	0.200	0.169	0	0.08	0.15	0.3	1	17
Penalty rate	fraction	0.389	0.907	0	0.10	0.15	0.3	15	26
Personal Characteristic:									
Age	years	56.490	13.8	20	48	58	67	90	0
Black-African American	percent	8.45%	--	--	--	--	--	--	1
Native American	percent	1.36%	--	--	--	--	--	--	1
Asian	percent	2.33%	--	--	--	--	--	--	1
Other Race	percent	5.83%	--	--	--	--	--	--	1
hispaniclatino	percent	14.67%	--	--	--	--	--	--	0
male	percent	44.12%	--	--	--	--	--	--	0
married	percent	59.38%	--	--	--	--	--	--	0
education	percent	49.76%	--	--	--	--	--	--	0
foreignborn	percent	10.79%	--	--	--	--	--	--	0
Marginal Tax Rate	fraction	0.172	0.079	0	0.15	0.15	0.25	0.33	94
self-employed	percent	17.30%	--	--	--	--	--	--	438
Social Network Characteristics:									
prop_altersaudited	fraction	0.029	0.083	0	0	0	0	0.9	16
prop_alters_talkTaxes	fraction	0.279	0.280	0	0	0.2	0.5	1	16
prop_alterselfemployed	fraction	0.206	0.225	0	0	0.1	0.3	1	16
Experiences:									
hheveraudited	percent	20.21%	--	--	--	--	--	--	39
haventfiledtaxes	percent	3.11%	--	--	--	--	--	--	38
preptaxesself	percent	39.55%	--	--	--	--	--	--	39
Attitudes, beliefs, and views:									
prob_deduction	fraction	0.294	0.319	0	0	0.2	0.5	1	38
actor_more	percent	20.99%	--	--	--	--	--	--	40
freeriding_never	scale of 0-5	2.54	1.15	0	2	2	3	5	40
freeriding_percentage	percentage	49.77	17.73	0	38	52	62	100	41
worthpayingtaxes	percent	56.76%	--	--	--	--	--	--	37
importancetaxbenefits	scale of 0-100	24.8	19.98	0	10	20	30	100	42
importancemoraloblig	scale of 0-100	23.7	25.11	0	0	20	35	100	42

APPENDIX H: The Evasion Rate Models Estimated without the Sampling Weights

Independent Variables	Mixed-Effects Model			Fractional Response Model			
	Coef.	S.E.	p-values	Coef.	S.E.	p-values	Average Marginal Effects
Perceived Rates and the Group Assignment:							
Tax rate	0.393	0.0559	<0.001	1.060	0.2368	0.000	0.223
randomtaxincrease	-0.038	0.0196	0.054	0.103	0.1106	0.352	0.022
randomtaxincrease*Tax rate	0.250	0.0692	<0.001	0.189	0.3214	0.557	0.040
Audit rate	-0.057	0.0200	0.004	-0.077	0.0949	0.417	-0.016
Penalty rate	-0.052	0.0133	<0.001	-0.045	0.0304	0.140	-0.009
Personal Characteristic:							
Age	-0.001	0.0006	0.073	-0.003	0.0025	0.208	-0.001
Black-African American	0.003	0.0270	0.917	0.076	0.1034	0.463	0.016
Native American	0.126	0.0576	0.028	--	--	--	--
Asian	-0.057	0.0485	0.240	-0.171	0.2023	0.398	-0.034
Other Race	0.030	0.0341	0.386	0.143	0.1508	0.342	0.031
hispaniclatino	0.011	0.0238	0.646	0.023	0.1121	0.835	0.005
male	0.034	0.0143	0.017	0.173	0.0647	0.007	0.037
married	-0.034	0.0144	0.017	-0.104	0.0679	0.125	-0.022
education	-0.013	0.0151	0.406	0.010	0.0701	0.885	0.002
foreignborn	0.006	0.0246	0.815	0.082	0.1126	0.468	0.018
Marginal Tax Rate	-0.258	0.0976	0.008	-0.176	0.4485	0.694	-0.037
self-employed	0.011	0.0186	0.557	0.032	0.0864	0.709	0.007
Social Network Characteristics:							
prop_altersaudited	0.045	0.0805	0.578	-0.005	0.3618	0.990	-0.001
prop_alters_talkTaxes	-0.025	0.0256	0.328	-0.070	0.1173	0.552	-0.015
prop_alterselfemployed	0.030	0.0326	0.364	0.083	0.1506	0.580	0.018
Experiences:							
hheveraudited	-0.012	0.0174	0.493	-0.115	0.0820	0.160	-0.024
haventfiledtaxes	0.049	0.0407	0.233	0.023	0.1581	0.886	0.005
preptaxesself	-0.014	0.0146	0.347	-0.099	0.0664	0.136	-0.021
Attitudes, beliefs, and views:							
prob_deduction	0.097	0.0223	0.000	0.451	0.1018	0.000	0.095
actor_more	0.028	0.0181	0.128	0.094	0.0773	0.222	0.020
freeriding_never	-0.010	0.0064	0.132	-0.044	0.0288	0.123	-0.009
freeriding_percentage	0.001	0.0004	0.055	0.006	0.0018	0.001	0.001
worthpayingtaxes	0.001	0.0142	0.928	-0.053	0.0667	0.424	-0.011
importancetaxbenefits	0.000	0.0004	0.921	0.001	0.0017	0.553	0.000
importancemoraloblig	0.000	0.0003	0.504	-0.002	0.0014	0.133	0.000
constant	0.228	0.0504	0.000	-1.656	0.2320	0.000	--
Num. of obs. = 5,159		Wald chi2(30) = 401.22		Num. of obs. = 5,084		Wald chi2(29) = 164.69	
Num. of resp. = 752		p-value < 0.001		Num. of resp. = 741		p-value < 0.001	

Appendix I: Regression Models That Were Used to Estimate the Impact of the Proposed Interventions on the Evasion Rate

Table I.1: Fractional Response Model of the Evasion Rate

(Sample is Limited to Only Those Who Prepare Their Tax Returns Themselves)

Independent Variables	Coeff.	S.E.	p-values	Average Marginal Effects
Perceived Rates and the Group Assignment:				
Tax rate	0.309	0.6220	0.620	0.185
randomtaxincrease	-0.112	0.2692	0.677	0.033
randomtaxincrease*Tax rate	1.038	0.8311	0.212	--
Audit rate	-0.200	0.3042	0.511	-0.038
Penalty rate	-0.065	0.0369	0.076	-0.013
Personal Characteristic:				
Age	0.011	0.0059	0.053	0.002
Black-African American	0.189	0.2416	0.434	0.038
Native American	--	--	--	--
Asian	--	--	--	--
Other Race	0.259	0.2390	0.279	0.054
hispaniclatino	0.293	0.2218	0.187	0.060
Male	0.196	0.1458	0.178	0.038
Married	-0.268	0.1674	0.109	-0.053
Education	-0.247	0.1653	0.136	-0.046
Foreignborn	0.252	0.3139	0.423	0.051
Marginal Tax Rate	-1.081	1.3292	0.416	-0.208
self-employed	-0.258	0.3169	0.415	-0.046
Social Network Characteristics:				
prop_altersaudited	0.622	0.6707	0.353	0.120
prop_alters_talkTaxes	0.009	0.2799	0.974	0.002
prop_alterselfemployed	0.830	0.3347	0.013	0.160
Audit Experience:				
hheveraudited	-0.398	0.2265	0.079	-0.071
Attitudes, beliefs, and views:				
prob_deduction	0.596	0.2492	0.017	0.115
actor_more	0.276	0.1832	0.133	0.055
freeriding_never	-0.134	0.0783	0.086	-0.026
freeriding_percentage	0.002	0.0032	0.499	0.000
worthpayingtaxes	-0.023	0.1677	0.891	-0.004
importancetaxbenefits	-0.004	0.0038	0.248	-0.001
importancemoraloblig	-0.006	0.0033	0.068	-0.001
Constant	-1.724	0.5598	0.002	--
Num. of obs. = 2,045			Wald chi2(26) = 181.31	
Num. of resp. = 299			p-value < 0.001	

NOTE: 1) The dependent variable is respondent's subjective probability of underreporting taxes. 2) The regression model was estimated with a winsorized data since the perceived penalty rate variable had several unusually large values. These extreme values were set to 99th percentile, which was 400%.

Table I.2: Fractional Response Model of the Evasion Rate

(Full Sample)

Independent Variables	Coeff.	S.E.	p-values	Average Marginal Effects
Perceived Rates and the Group Assignment:				
Tax rate	0.659	0.3239	0.042	0.189
randomtaxincrease	0.036	0.1530	0.812	0.035
randomtaxincrease*Tax rate	0.426	0.3985	0.285	--
Audit rate	0.113	0.1664	0.498	0.024
Penalty rate	-0.040	0.0440	0.369	-0.008
Personal Characteristic:				
Age	0.000	0.0030	0.913	0.000
Black-African American	-0.061	0.1371	0.656	-0.013
Native American	--	--	--	--
Asian	-0.443	0.2356	0.060	-0.081
Other Race	0.235	0.1748	0.178	0.053
Hispaniclatino	-0.085	0.1379	0.538	-0.018
Male	0.027	0.0909	0.765	0.006
Married	0.014	0.1046	0.890	0.003
Education	-0.018	0.1098	0.871	-0.004
Foreignborn	0.205	0.1553	0.186	0.045
Marginal Tax Rate	-0.723	0.6345	0.254	-0.153
self-employed	0.007	0.1581	0.964	0.002
Social Network Characteristics:				
prop_altersaudited	0.729	0.4652	0.117	0.154
prop_alters_talkTaxes	-0.238	0.1711	0.164	-0.050
prop_alterselfemployed	0.452	0.1932	0.019	0.095
Experiences:				
Hheveraudited	-0.266	0.1250	0.034	-0.053
Haventfiledtaxes	0.026	0.1788	0.885	0.006
Preptaxesself	-0.124	0.0975	0.203	-0.026
Attitudes, beliefs, and views:				
prob_deduction	0.609	0.1342	<0.001	0.128
actor_more	0.234	0.1149	0.042	0.051
freeriding_never	-0.054	0.0353	0.126	-0.011
freeriding_percentage	0.006	0.0023	0.006	0.001
Worthpayingtaxes	-0.114	0.0922	0.217	-0.024
importancetaxbenefits	0.003	0.0021	0.221	0.001
importancemoraloblig	0.000	0.0021	0.949	0.000
Constant	-1.863	0.3071	<0.001	--
Num. of obs. = 5,084			Wald chi2(29) = 202.49	

Num. of resp. = 741	p-value < 0.001

NOTE: 1) The dependent variable is respondent's subjective probability of underreporting taxes. 2) The regression model was estimated with a winsorized data since the perceived penalty rate variable had several unusually large values. These extreme values were set to 99^{th} percentile, which was 400%.

Appendix J: The Estimated Effects of the Interventions If They Impacted Everyone, And Not Only Those Who Prepare Their Tax Returns Themselves

Table J.1: Estimated Effect of the Interventions on the Evasion Rate, if They Affected Everyone Perfectly (i.e., all misperceptions were eradicated completely)

	No intervention	**Intervention 1 only**	**Intervention 2 only**	**Both Interventions**
Predicted Evasion Rates	24.55%	20.60%	24.37%	20.44%
Reduction in Evasion Rates (in percentage points)	--	3.95	0.18	4.11

NOTES: A fractional response model was used to estimate the evasion rates. The regression output for the model is presented in **Table I.2**, **Appendix I**.

Table J.2: Estimated Additional Tax Revenues That Could be Collected Due to the Interventions if They Affected Everyone, Assuming Different Levels of the Intervention Effectiveness (i.e., *f*)

Levels of the Intervention Effectiveness (the effectiveness factor, *f*)	**Additional Tax Revenues*** (in billions of dollars)		
	Intervention 1 only	**Intervention 2 only**	**Both Interventions**
100% (*f* = 1)	44.4	2.0	46.2
80% (*f* = 0.8)	35.5	1.6	37.0
60% (*f* = 0.6)	26.6	1.2	27.7
40% (*f* = 0.4)	17.8	0.8	18.5
20% (*f* = 0.2)	8.9	0.4	9.2
10% (*f* = 0.1)	4.4	0.2	4.6

NOTE: * -Both underreporting and non-filing tax gaps for individual income were considered. In other words, *G* in formula (4.1) was equated to ***$276*** billion, of which $245 billion is underreporting tax gap and $31 billion is non-filing tax gap. The tax gap estimates were taken from *Federal Tax Compliance Research: Tax Gap Estimates for Tax Years 2011-2013* report (IRS, 2019b).