# Culture, Compliance, and Confidentiality: Taxpayer Behavior in the United States and Italy

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**Highlights**

- The threat of public disclosure of tax evasion may act as a non-financial penalty.
- However, public disclosure could crowd out intrinsic motivations for compliance.
- This paper uses laboratory experiments to examine the impact of confidentiality.
- Identical experiments in the United States and Italy are conducted.
- We find public disclosure increases compliance, mainly on the extensive margin.

**Abstract:**
This paper analyzes the impact of confidentiality of taxpayer information on the level of compliance in two countries with very different levels of citizen trust in government – the United States and Italy. Using identical laboratory experiments conducted in the two countries, we analyze the impact on tax compliance of "Full Disclosure" (e.g., release of photos of tax evaders to all subjects, along with information on the extent of their non-compliance) and of "Full Confidentiality" (e.g., no public dissemination of photos or non-compliance). Our empirical analysis applies a two-stage strategy that separates the evasion decision into its extensive (e.g., "participation") and intensive (e.g. "amount") margins. We find strong support for the notion that public disclosure acts as an additional deterrent to tax evaders, and that the deterrent effect is concentrated in the first stage of the two-stage model (or whether to evade or not). We also find that the deterrent effect is similar in the U.S. and in Italy, despite what appear to be different social norms of compliance in the two countries.

**Keywords:** Tax compliance, experimental economics, confidentiality, social norms.

## 1. Introduction

National tax administrations are constantly looking for innovative and cost-effective ways to increase tax compliance, beyond the traditional compliance-inducing measures of increased penalty and audit rates. A novel method that has been increasingly discussed is limited disclosure of taxpayer information in cases of tax evasion. The threat of public "shame" through disclosure adds a non-financial penalty that may induce taxpayers to increase compliance to keep their names clean. However, the threat of public disclosure could instead crowd out intrinsic motivations for compliance, and thereby reduce compliance as a retaliatory action. Disclosure may also increase utility for a subset of individuals who hold a strong anti-tax sentiment, an effect that may be reinforced if "contagion" effects exist wherein observing that others have underreported income may reduce one's own compliance. All of these effects may depend on the way in which the psychological costs of shame enter the decision to evade, either as a fixed component or a variable component. Therefore, whether and how public disclosure of taxpayer compliance behavior affects compliance cannot be predicted a priori, and the little systematic evidence of its effects shows somewhat conflicting results. This paper uses a cross-country laboratory experiment to examine the impact of confidentiality of taxpayer information on the level of individual compliance in two settings in which baseline taxpayer attitudes and compliance are arguably different – Italy and the United States.

We first develop a simple model that extends the standard economics-of-crime model of tax evasion (Allingham and Sandmo, 1972) by incorporating a "social norm" of compliance by which taxpayers experience a psychological loss when they violate the norm, following the approach of Alm and Torgler (2011). Public disclosure affects the psychological cost of violating the norm, but disclosure can either increase or decrease the cost, inducing either more or less compliance than under full confidentiality. These conflicting effects occur because the psychological cost of violating social norms is assumed to have both a variable component that depends on the amount evaded and a fixed component that does not.

We then test the model using experiments and applying an empirical estimation strategy that separates the decision of whether to evade or not (e.g., the extensive margin, or "participation") and from the decision of how much to evade (e.g., the intensive margin, or "amount"). Consistent with the notion of a fixed psychological cost of non-compliance, we find strong support for the idea that public disclosure acts an additional deterrent to tax evaders. We also find that the deterrent effect is concentrated in the first stage of the two-stage model (or whether to evade or not). Further, we find that the deterrent effect is similar in the U.S. and in Italy, despite what appear to be different social norms of compliance in the two countries. Finally, we show that this fixed cost is important to measure properly the impact of traditional policy instruments on compliance. Indeed, we demonstrate that empirical approaches that ignore the fixed component are likely to overestimate the effect of standard deterrence instruments.

The impact of explicit disclosure of evasion has seldom been empirically studied at the individual level due largely to the absence of reliable micro-level taxpayer data. Even so, there are some studies that have analyzed the impact of disclosure in naturally occurring environments. Bø, Slemrod, and Thoresen (2015) exploit a natural experiment in Norway, where tax data were made available on the internet after 2001. They found on average a slight increase in reported business income after 2002 in communities that previously had limited disclosure. Also, Hasegawa et al. (2013) analyzed disclosure of individual and corporate tax information in Japan, and found that the existence of a "disclosure threshold" encouraged some underreporting of income. Perez-Truglia and Troiano (2015) conducted a field experiment to study the effect of increasing the publicity of online lists with names, tax debts, and other information of tax delinquents maintained in three U.S. states (Kansas, Kentucky, and Wisconsin). They found that increasing the salience of the list by informing neighbors of tax delinquents increased the probability of tax delinquents paying the tax debt in cases of moderate debt (a tax debt lower than $2,274), but not in cases of higher debt.

Some laboratory experiments have also looked at the effects of disclosure on taxpayer compliance, with mixed results. Laury and Wallace (2005) conducted a laboratory experiment that implemented a mild form of disclosure and found some suggestive evidence that disclosure has a positive effect on compliance. Fortin, Lacroix, and Villeval (2007) also studied the effects of feedback on tax reporting decisions. In their design, subjects were told the number of subjects who underreported income in the previous round and the mean level of reported income. They found that reported income was slightly lower when subjects received information on others' reporting behavior, but also that an increase in the average level of evasion in the group was associated with an increase in individual reported income. Lefebvre et al. (2011) compared tax reporting behavior across three countries (France, Belgium, and the Netherlands). They found that subjects who observed "bad" examples (e.g., a minimum proportion of subjects reporting truthfully) were less likely to fully report income, but that subjects who saw “good” examples (e.g., a maximum proportion of subjects reporting truthfully) were largely unaffected. They also found differences in reporting across countries, with underreporting more common in France and the Netherlands than in Belgium. Coricelli et al. (2010) focused on the emotional impact of cheating and disclosure in a tax-reporting experiment. In a “pictures” treatment, a subject who was audited and found to have unreported income had his or her photo shown to others in the session. They found higher compliance in their photos treatment, as well as increased “emotional arousal”, as measured by skin conductance responses; they also found higher compliance (and higher emotional arousal) after an audit. Casal and Mittone (2016) studied the effect of shaming in various settings in which taxes payments were redistributed to subjects as in public good games. They found some complex types of behavior in which the effect of shaming tax evaders tends to increase compliance. In contrast, Casagrande et al. (2015) did not find any effect of shaming in a random audit game.

Despite these innovative contributions, the impact of disclosure or confidentiality on taxpayer compliance remains unresolved. In particular, there are several important questions about the impact of confidentiality on compliance that are unanswered. First, how does confidentiality affect the decision to evade or not? Second, how does confidentiality affect the decision on how much to evade? Third, do these impacts vary across cultures?

We seek to answer these questions by using laboratory experiments to examine the impact of disclosure in two quite different environments – the United States and Italy. In our cross-country experimental design, an individual is given income, and then must decide how much of the income to report. Taxes are paid on reported income at a preannounced tax rate, and no taxes are paid on unreported income. However, unreported income may be discovered via an audit, and the subject must then pay the unpaid taxes plus a fine based on the unpaid taxes. We introduce two main treatments. In one treatment (“Full Confidentiality”), an individual who is detected evading is financially penalized, but his or her reporting information is not shared with the other subjects. In a second treatment (“Full Disclosure”), those who have been caught evading find their non-compliance information shared among the subjects via the display of their picture on the computer screens of all subjects, along with information on their level of underreporting. Our full disclosure treatment is designed to mimic attempts by some tax authorities to use the threat of shame to encourage tax compliance.

Unlike Coricelli et al. (2010), in our photos treatment both the photo and reported income of all subjects who were caught cheating via audit were displayed on all subject computers. Because our goal is to explore how this type of disclosure affects tax compliance, we e avoid treatments (such as an endogenous audit probability) that could be expected to reduce the stigma associated with evading taxes. In this sense our motivation and procedures are more like those used by Casal and Mittone (2016), whose public goods design likely gave shaming its best shot at increasing compliance. However, it is not obvious that most taxpayers view paying taxes as an efficiency-enhancing positive-sum game. In fact, anecdotal evidence suggests that some taxpayers may view tax payments as reducing efficiency rather than as even a zero-sum game. In our experiment, we omit this public goods aspect of the experiment. Thus we can observe whether disclosure of this sort improves compliance in an environment in which individuals do not necessarily view their tax payments as contributing to a public good.

Importantly, we conduct separate but identical experiments in the U.S. and in Italy, providing us with different baselines of compliance norms. By performing mirror experiments, we are better able to identify the marginal impact of public disclosure on compliance behavior than would be possible by focusing on just one country. We also employ an estimation strategy that allows us to assess the relative impact of public disclosure both on the likelihood that an individual may evade taxes and (for those who are not fully compliant) on the extent to which they evade.

We find strong support for the notion that public disclosure acts as an additional deterrent to tax evaders. We also find that the deterrent effect is concentrated in the first stage of the two-stage model (or whether to evade or not). Finally, we find that the deterrent effect is similar in the U.S. and in Italy, despite what appear to be different social norms of compliance in the two countries.

Overall, our results speak to several important and growing literatures regarding tax compliance and culture, social norms, and non-pecuniary behavioral interventions. In doing so, we confirm the potential of public disclosure as an instrument to encourage compliance.

The paper is organized as follows. Session 2 presents the institutional practices followed in the U.S. and in Italy to manage taxpayer information. Section 3 presents a theoretical model to study the effect of confidentiality on taxpayers' compliance. Section 4 discusses the experimental design. The results of the experiment are presented in Section 5. Section 6 concludes.

## 2. The Institutional Context

The United States and Italy have very different institutional perspectives on the role of confidentiality in disclosure and tax compliance. In the U.S., announcing the names of federal tax evaders is a departure from the standard of practice of maintaining confidentiality of individual taxpayer data, in which confidentiality is a long-held basic right of the U.S. federal tax system. [1] Section 6103 of the Internal Revenue Code sets the guidelines for confidentiality and for the limited disclosure of return information to state and local tax officials. As noted by former Internal Revenue Service (IRS) Commissioner Margaret Richardson, "IRS employees are prohibited from accessing information not needed to perform their official tax administration duties" (Testimony, 15 April 1997). Confidentiality of taxpayer data is thereby guaranteed within the system of tax administration, and the IRS imposes strict disclosure rules for individual taxpayer data flowing outside the federal system to state tax administrators, other U.S. government agencies, individuals, and companies. The IRS also imposes penalties for unwarranted disclosure.

While taxpayers may believe that IRS rules ensure that tax information is largely private and held in confidence by the IRS, the confidentiality of taxpayer data and information has not always been a given. Until the mid-1970s, tax returns of publicly traded companies were available to the public at-large. Some U.S. states have utilized a "wall of shame" approach to increase voluntary compliance. For example, the revenue code of the state of Georgia allows limited disclosure in certain cases of tax arrears. In West Virginia disclosure of corporate income tax returns may occur once disputes in liabilities reach the point of the circuit court. Taxpayers themselves have sometimes voluntarily chosen to make their returns public; indeed, many in political office choose to do so. The level of disclosure and taxpayer reaction therefore falls along some continuum from subtle to extremely overt.

In contrast, Italy's attitudes towards tax evaders are surprisingly mixed. Estimates from various sources indicate that evasion in Italy is much higher than in other highly developed countries (Giovannini, 2011), and Italy is often characterized as having particularly acute problems with tax evasion.[2] Further, this evasion is often considered the root of many problems

[1] This is different from the practice followed by some U.S. states of mantaining lists on the internet of tax delinquents (Perez-Truglia and Troiano, 2015).
[2] As an example, see an article from *The Economist Blog*, which starts by noting that "Death may be certain in Italy, but taxes are another matter: an estimated of € 285 billion remained unpaid last year, about 18% of GDP"

within the Italian economy, such as revenue loss, equity concerns, and other inefficiencies (Santoro, 2010). Even so, the Italian attitude towards tax evaders is more tolerant than one might expect. Social surveys consistently find that Italians report an index of tax morale significantly lower than in many other countries (Alm and Torgler, 2006; Cannari and D'Alessio, 2007).

Ambivalent Italian attitudes towards tax evasion also emerge from the way in which disclosure of taxpayers' information is both treated by the law and perceived by the public. In principle, Italian law allows for ample disclosure of individual taxpayer data. The law establishes that every year the tax administration compile lists with the names of all Italian taxpayers, their total income, their taxable income, and their major sources of income. The lists are then made available by the Italian Tax Agency ("Agenzia delle Entrate") and the taxpayers' municipalities to anyone who is interested. The standard practice has been that local and national newspapers occasionally access the lists and publish the names and incomes of wealthier people. This sometimes occurs for tax evaders as well. An issue that has raised concern recently is whether the Tax Agency or the municipalities can publish this information on their own. The problem exploded in 2008 when the Tax Agency published an internet list of *all* Italian taxpayers that could be accessed by everyone directly from his or her computer. This decision by the Tax Agency inflamed public opinion, which was split between privacy advocates and supporters who argued that the publication of the data could finally undermine the prevailing system of tax evasion. The list remained available only for few hours since the Italian Data Protection Authority declared the publication illegitimate, complaining both of the lack of explicit permission in the Italian law and of a more general problem of the disparity between the need for public transparency on taxpayer data and the ability to make them available in the web.

Following this episode, there have been other discussions in the Italian media and in political circles on the opportunity to make individual taxpayers' data more generally available, but without much effect. As a result, the situation in Italy is that information regarding taxpayers and tax evaders is only occasionally made available by local and national newspapers.

## 3. Theoretical Background

As discussed in Alm and Torgler (2011), models of tax compliance typically follow an Allingham and Sandmo (1972) economics-of-crime approach, in which a taxpayer decides how

(http://www.economist.com/blogs/schumpeter/2013/01/tax-evasion-italy ).

much income to report to tax authorities given that underreporting may be discovered and penalized.[3] The taxpayer's choice over how much of income ($I$) to declare ($D$) is a function of the parameters (or the audit probability rate $p$ and the penalty rate $f$), along with the tax rate $t$. It is straightforward to demonstrate that declared income increases with an increase in the audit rate or in the penalty rate; an increase in the tax rate has an ambiguous effect on declared income, dependent on attitudes toward risk.

This economics-of-crime approach implies that compliance depends upon enforcement. Indeed, this approach concludes that truthful reporting occurs *solely* because of the economic consequences of detection and punishment. This is certainly a plausible starting point. However, many researchers have concluded the compliance decision is not the same as the "gamble" portrayed by the Allingham and Sandmo (1972) approach. These researchers suggest that there are other factors beyond enforcement that also affect the individual's compliance decision (Graetz and Wilde, 1985; Elffers, 1991; Kirchler, 2007; Slemrod, 2007; Torgler, 2007), and there have been extensions of the basic model to incorporate these other factors.

One such extension has been to include "social norms". Although difficult to define precisely, Elster (1989) suggests that social norms can be distinguished by the feature that, unlike the outcome-orientation of individual rationality, they tend to be process-oriented. These norms therefore represent patterns of behavior that are judged similarly by others and are sustained in part by social sanction or condemnation. Consequently, when others behave according to some socially accepted mode, the individual will behave appropriately as well; if others do not so behave, then the individual will respond in kind (Frey and Torgler, 2007). Bicchieri (2006) defines norms somewhat differently, in which individuals adhere to norms because they believe that other people expect them to do so; see also Hausman (2008), who argues that notions of fairness need to be added to the Bicchieri (2006) framework.

Regardless, the presence of these social norms is consistent with approaches that emphasize that the nature of one's social interactions with others affects one's own compliance decision. These approaches introduce such additional considerations as altruism, reciprocity,

[3] See Cowell (1990), Andreoni, Erard, and Feinstein (1998), and Slemrod and Yitzhaki (2002) for comprehensive surveys of the evasion literature. See Alm (2012) and Sandmo (2012) for more recent discussions.

empathy, sympathy, trust, patriotism, customs, and intrinsic motivation into the individual compliance decision. Especially important considerations are guilt, shame, and morality.[4]

Overall, these broadly defined factors of taxpayer morality suggest that individuals will comply so long as they believe that compliance is the “right thing to do”. Conversely, we consider contagion effects, where if noncompliance becomes pervasive, then the ethics of compliance disappear or are even reversed (Myles and Naylor, 1996; Fortin, Lacroix, and Villeval, 2007; Traxler, 2010). This perspective also suggests that disclosure of one’s tax reporting choices to others may affect the social norm of compliance and, through this channel, each individual’s tax reporting decision.

One way to incorporate the role of morality is to assume that individuals have a social norm to obey the tax law, which has an effect similar to the “reference point” of Kahneman and Tversky (1979) in their prospect theory. In this approach, an individual experiences a loss in utility when he or she does not achieve the reference point, but the individual may avoid the loss by reporting all income and paying all taxes.

More formally, we extend the approach outlined in Alm and Torgler (2011), by assuming that each individual has a utility function defined by $U(I;C)$. The first part of the utility function is income $I$, and the second part represents the disutility of violating the social norm, represented by a psychological cost of cheating $C$. There are two potential states of the world: *Caught Underreporting*, where income is defined as $I_C$ in equation (1), and *Not Caught Underreporting*, where income is defined as $I_N$ in equation (2):

(1) $I_C=I-tD-f[t(I-D)]$

(2) $I_N=I-tD,$

where $I=D+E$ and where $E$ denotes evasion. Importantly, we extend Alm and Torgler (2011) by now assuming that the psychological cost of cheating $C$ may come in two forms: as a fixed cost and as a cost related to the amount of evasion $E$ as in equation (3):

(3) $C= K + \gamma E$

where $\gamma>0$ and where the fixed cost $K$=0 whenever $D=I$ and $K$>0 whenever $D$<I.

[4] For example, see Benjamini and Maital (1985), Cowell and Gordon (1988), Gordon (1989), Erard and Feinstein (1994), Myles and Naylor (1996), Kim (2003), Fortin, Lacroix, and Villeval (2007), and Traxler (2010) for examples of theoretical analyses that incorporate these notions. See Hashimzade, Myles, and Tran-Nam (2013) for a survey.

The individual now chooses declared income $D$ to maximize expected utility as defined in equation (4):

(4) $EU(D,C)=pU(I_C\ ;C)+(1-p)U(I_N\ ;C)$.

where $E$ denotes the expectation operator.

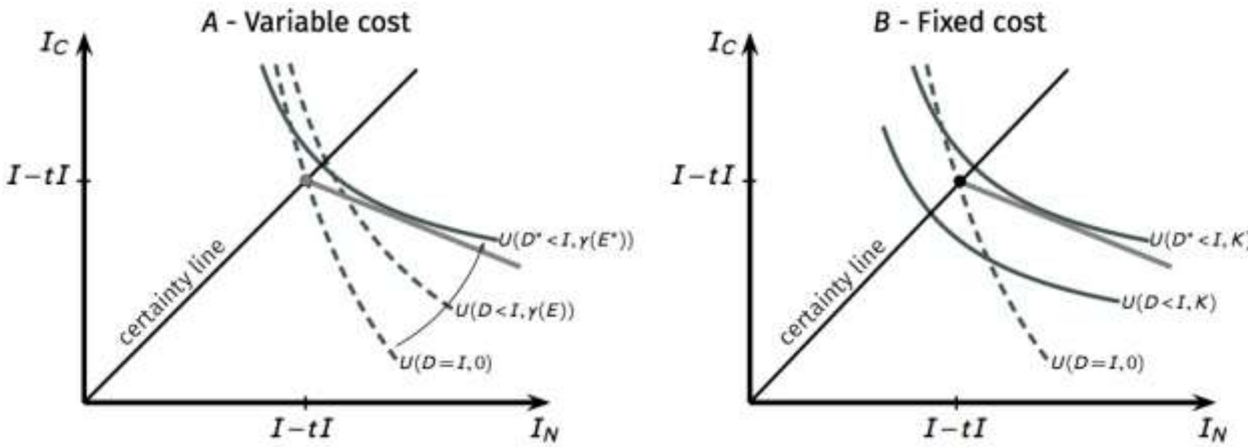
Note that other models in the literature have considered either fixed or variable moral costs of evasion (Benjamini and Maital, 1985; Gordon, 1989). However, little attention has been previously devoted to discussing and empirically analyzing the different effects of the two cost components. In particular, while it is straightforward to give conditions that declared income is higher in a setting with either component of cost than in the basic economics-of-crime model, there are important differences in the effects of the two components. These differences are illustrated in Figure 1, which shows the taxpayer indifference curves in the space of income under the two states of the world (e.g., caught versus not caught), for various levels of reported income $D$ (or equivalently, evasion income $E=I-D$).[5] The analysis assumes that the utility $U(I;C)$ is increasing and concave in the first argument, so that the first partial derivative on income is positive ($U_I>0$) and that the second partial derivative on income is negative ($U_{II}<0$); the analysis also assumes that utility is decreasing and concave in the second argument, so that $U_C<0$ and $U_{CC}<0$. Finally, the analysis assumes that the sign of $U_{IC}$ is such that an increase in the psychological cost $C$ increases optimal reported income [6] and also that the overall expected marginal utility of the taxpayer is increasing in underreporting (at least on $0\leq D\leq I$). This last assumption is necessary to ensure that the second-order condition of the taxpayer maximization problem is always satisfied, or that $\partial^2\mathcal{E}U(D)/\partial D^2\partial D<0$.[7]

[5] See Appendix A for a full mathematical treatment.

[6] Previous analyses by Benjamini and Maital (1985) and Gordon (1989) have assumed that $U_{IC}=0$. In the case in which $C$ includes only the fixed cost $K$, the restriction $U_{IC}=0$ implies that an increase in $K$ has no effect on the internal solution and that $K$ only makes the corner solution $E=0$ more likely. It is shown in Appendix A that a necessary and sufficient condition for $\partial D/\partial K>0$ (and also at an internal solution) is $[U_{IC}(I_N,C)U_I(I_C,C)-U_{IC}(I_C,C)U_I(I_N,C)]<0$. The same condition is sufficient (even if not necessary) when the cost $C$ reduces to the variable component only.

[7] Note that, if $\partial^2\mathcal{E}U(D)/\partial D\partial D$ is positive on some range and negative on some other range, then there may be multiple local maxima, and the global optimum needs to be determined comparing the utility level in all local maxima.

**Figure 1: The Decision to Evade with Variable and Fixed Psychological Costs**




Both panels report the indifference curves of the utility function of the taxpayer. The gray line is the budget line. In Panel A, with variable cost, the indifference curves twist smoothly for the different levels of *E=I-D;* in Panel B, with fixed cost, the indifference curves pivot abruptly and once for all between D=I and D<I due to a sudden change of K (from K=0 to K>0).

The diagram in Panel A shows the effect on the indifference curves of the *variable* component of the psychological cost of cheating, or when *C* of equation (3) reduces to *γ(E)*. A decrease in compliance from *E*=0 (or *D*=*I*) to *E*>0 (or *D*<*I*) pivots the indifference curves counter-clockwise through *γ*. The changes in the slope of the indifference curves occur smoothly at all evasion levels, including between the intensive and the extensive margins of the compliance decision. The diagram in Panel B shows the effect of the *fixed* cost component *K*, or when *C* reduces to 0 for *D*=*I* and *C*=*K*>0 for *D*<*I*. The fixed cost introduces an abrupt twist in the indifference curves between E=0 and E>0. In this case, the taxpayer's optimal decision must be obtained in two steps: first, a local optimum is determined for *D*<*I* (and *C*=*K*); second, the utility at the local optimum is compared with the utility at full compliance *I*=*D* with *C*=0 to determine the global maximum. Due to the fixed cost *K* when *D*<*I,* the overall optimum may jump between full compliance and a large level of evasion.

This analysis clearly implies that the two psychological components of the cost of cheating have very different implications for tax evasion. First, there may be factors influencing the fixed cost and the participation decision that do not affect the amount decision. For example, while in Gordon (1989) the cost *C* is due to a private stigma that damages self-image depending on the amount of income that is concealed, for other taxpayers *C* may come as a pure fixed cost for various reasons: because the feeling of guilt depends only on the act of breaking the rule and not on the extent of the violation; because guilt is due to a general sense of anxiety related to the decision to be a tax cheater creating perhaps also a sense of "arousal" as in Coricelli et al. (2010); or simply because guilt is caused by the psychic cost to enter in a condition of uncertainty (in which case it also resembles the notion of preference for certainty). Second, the possibility of fixed psychological costs must be handled appropriately when compliance behavior is studied empirically, since it may also affect the impact estimated for the other traditional policy instruments, as discussed later. Finally, there may be different effects of guilt in the aggregate. For example, with the addition of a fixed cost to the overall psychological cost, the problem of economic inequality caused by tax evasion between those who fully comply with the tax law and those who make large evasion decisions is amplified relative to the basic economics-of-crime model and also relative to the case with the variable psychological cost only.

Importantly, both $\gamma$ and $K$ may be sensitive to the disclosure of one's compliance behavior to others; that is, both parameters may vary with the amount of confidentiality. The effect can work through several channels. For example, $\gamma$ and/or $K$ are likely to be sensitive to the public disclosure through social stigma. The stronger the ethical norm to pay one's taxes fully, the more deviant the behavior of a non-compliant individual becomes, and the more loss that the individual feels with disclosure. Cultural and personal values can also affect the strength of the norm under public disclosure. The effect of public disclosure could be weaker in societies where private values like family and friendship are more important, while disclosure could be stronger in societies in which civic values like justice and politics are rated higher. Religions that encourage forgiveness may reduce the effect of disclosure on compliance, while faiths that put less weight on mercy and more on individual responsibility could enhance the effect of disclosure.

Of course, disclosure could instead lead to a decline of $\gamma$ and/or $K$ if noncompliance is viewed as a legitimate form of government protest. There are several reasons why this may occur. Some work has emphasized that, if taxpayers perceive that services provided by the public sector in return for taxes are not "fair", then taxpayers may respond by increasing evasion as a form of civic protest (Mason and Calvin, 1984; Cowell and Gordon, 1988; Bordignon, 1993; Rablen, 2010). In this case, public disclosure could make taxpayers even more aggressive, which in the context of equations (1) and (2) implies lower values for $\gamma$ and/or $K$. A decline in $\gamma$ and/or $K$ following disclosure could also be due via a "contagion" effect such that observing that others have underreported income may reduce the overall compliance rate.

This discussion illustrates the complexity of the compliance effects of confidentiality. As emphasized earlier, the actual evidence on confidentiality versus disclosure is not clear-cut. The next section presents our experimental design to examine this issue.

## 4. Experimental Design

We use a laboratory experiment to analyze the impact of public disclosure of tax evasion, using identical experiments in Italy and in the United States. Experimental methods have long been used to study compliance. They allow many factors suggested by theory to be introduced in experimental settings, they allow these factors to be introduced singly and exogenously in a controlled environment, and they generate precise data on individual compliance behavior. There are also legitimate concerns regarding small sample sizes and the use of student subjects, concerns that relate to the “external validity” validity of laboratory experiments. Still, there is now much evidence that there is little difference between student and nonstudent responses in most environments (Plott, 1987), including evidence that relates directly to compliance behavior (Alm, Bloomquist, and McKee, 2015).[8] Most importantly, there is now a large literature (Smith, 1976, 1982) that argues convincingly that experimental methods can contribute significantly to policy debates, as long as some conditions are met: the payoffs to subjects must be salient, decision costs must be commensurate with the payoffs, and the experimental setting must capture the essential properties of the naturally occurring environment that is the subject of investigation. These conditions are met in our experimental design.

Our basic experimental design follows that typically used in previous tax compliance experiments (Alm and Jacobson, 2007; Alm, 2010).[9] An individual is given income, and then must decide how much of the income to report. Taxes are paid on reported income at a preannounced tax rate of 30 percent, and no taxes are paid on unreported income. Unreported income may be discovered via an audit. If the subject is audited and found to have underreported income, the subject must then pay the unpaid taxes plus a fine based on the unpaid taxes at a preannounced penalty. There is no public good financed by tax payments in the experiment.[10]

[8] However, see Choo, Fonseca, and Myles (2016) for experimental results that demonstrate some differences between student and non-student responses.
[9] A copy of the experimental instructions is in Appendix B.
[10] The main reason for the absence of a public good is to reduce effects due to strategic interactions in small groups that would arise when the tax revenues collected in the lab are used to finance a public fund that is either divided between the subjects of the experiment or even given to a public fund or a charity. Nevertheless, we acknowledge

**Figure 2: Tax Filing Decision**

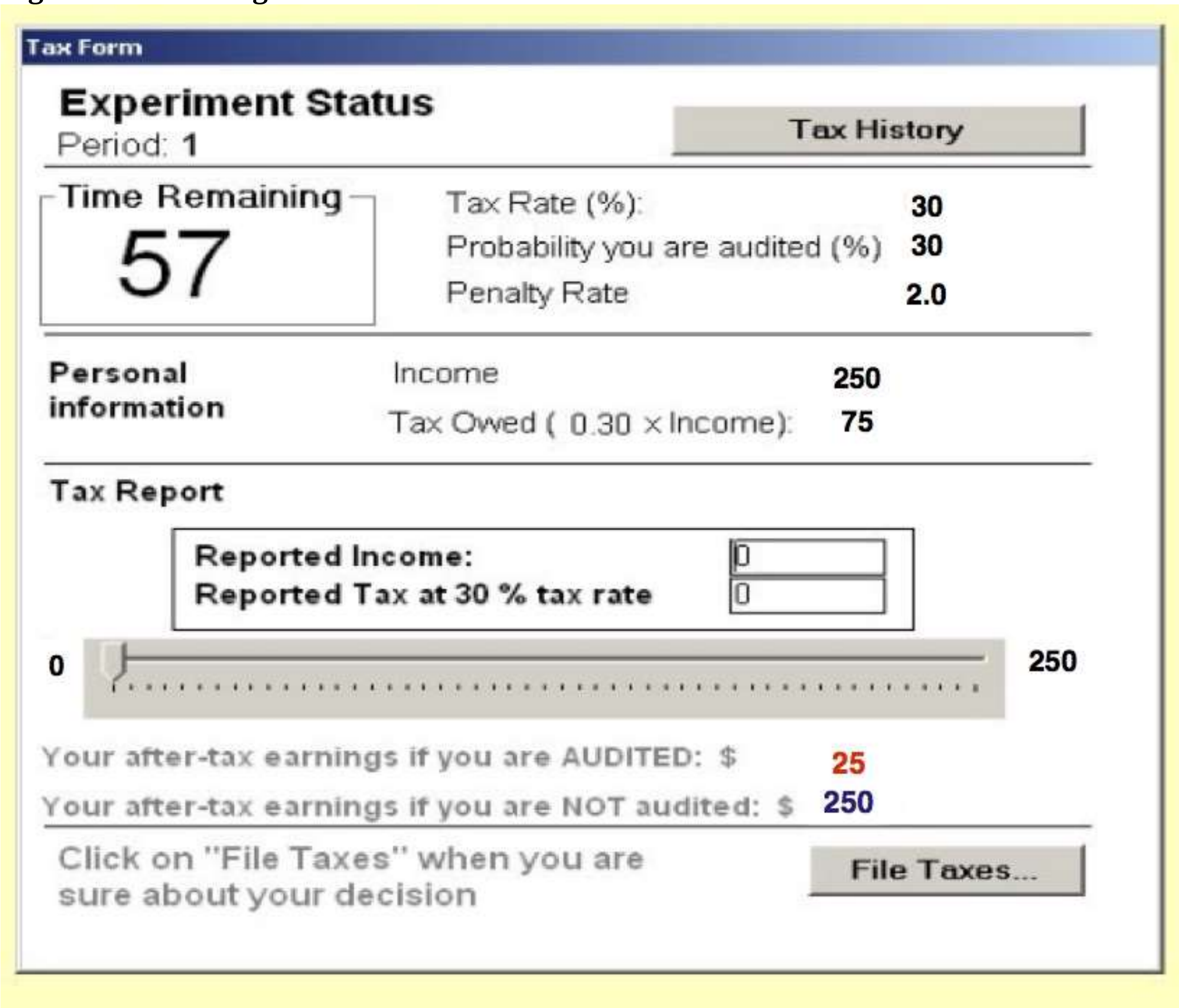
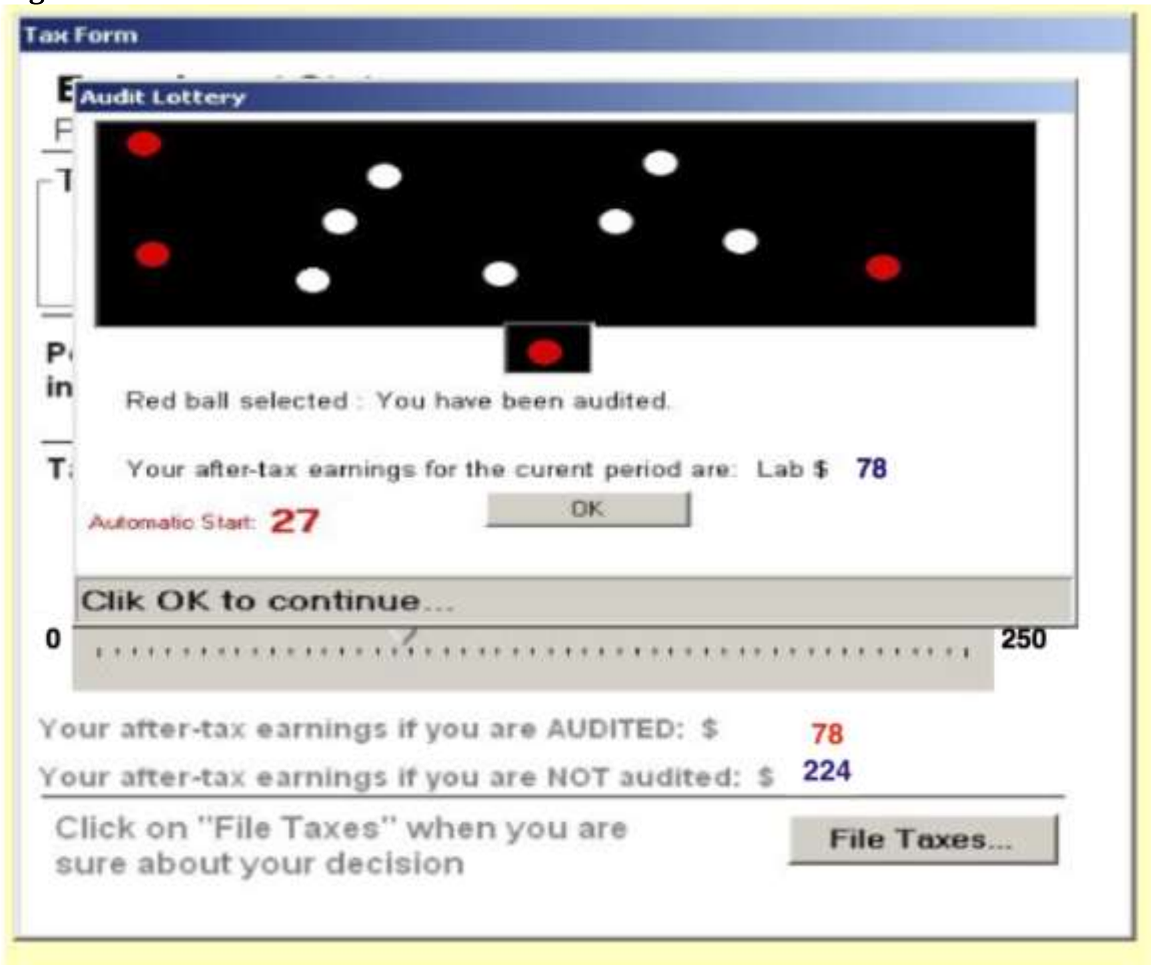


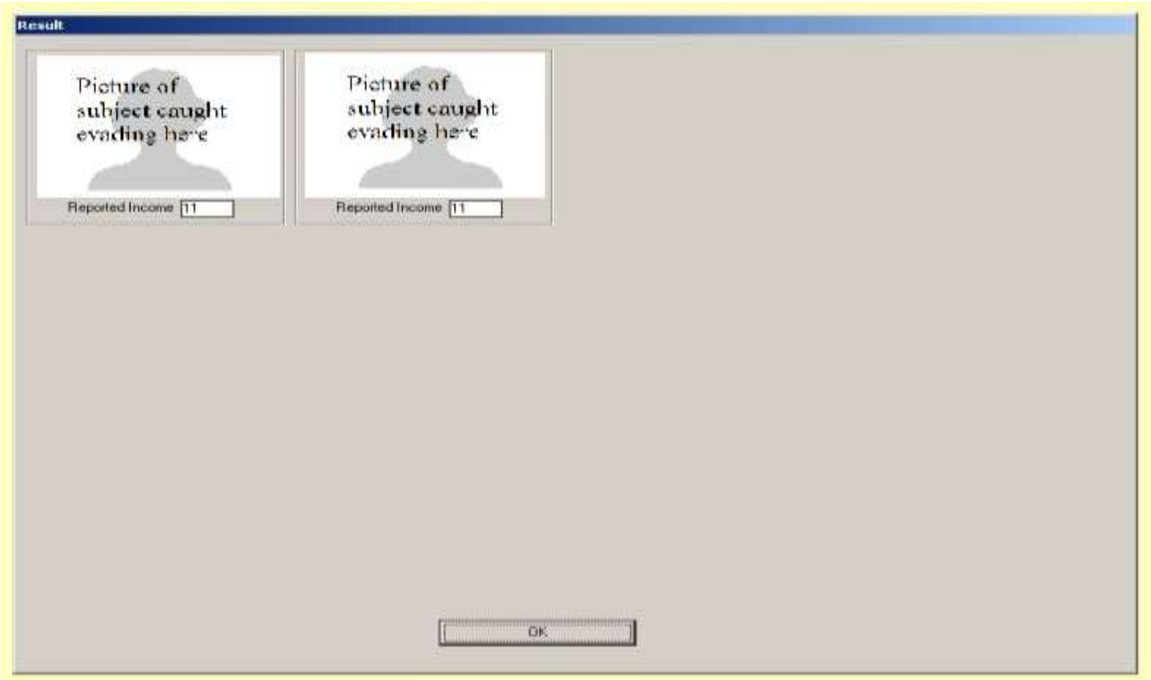

Figure 2 shows a sample screenshot from the filing decision in our experiment. The computer interface displays the tax rate, the probability of an audit, the penalty rate, income, and the tax owed.[11] Subjects used the scroll bar to enter a tax reporting decision, with the chosen amount of income (and associated tax payment) shown in the boxes above the scroll bar. The subject's earnings (whether or not audited) were also shown for any level of income indicated. Subjects were able to revise their choice by sliding the scroll bar to different levels of income. The resulting earnings (if audited or if not audited) were updated and displayed for any level of

that this procedure may induce among participants a perception of unfair or inefficient taxation, with an effect that could partly even vary between countries, since people of different countries have different experiences concerning the way in which tax revenues are used.

[11] A countdown timer was displayed on subject's computer screen, but the time limit was not enforced. Most reporting decisions were made quickly, almost always before the timer reached zero. In those cases when the time expired, subjects still were able to enter their decision. The tax history button allowed a subject to view his or her own tax reporting decisions, the audit outcomes, and the period earnings from all prior rounds of the experiment.

**Figure 3: Audit and Post-audit Information**



income selected. Thus the earnings implications for any possible reporting decision were transparent and easily available to the subject. The choice was only finalized when the "File Taxes" button was clicked. After all subjects did so, the audit outcome was randomly determined independently for each individual according to the pre-announced audit probability. The computer screen then displayed the subject's earnings for that period (the top panel of Figure 3).

Each subject chose how much income to report in 16 rounds. Period earnings were revealed at the end of each round. However, the subject's final earnings for the experiment were based solely on the earnings from one round. The round used for payment was randomly selected at the end of the session based on a single throw of a 16-sided die. Subjects were then privately paid their earnings from this one round only (plus a fixed participation payment). All decisions were conducted on computers, with each subject assigned to his or her own computer. All computer screens were visually isolated from the others' computers.

Income was held constant ($25 in the U.S. and €15 in Italy), as was the tax rate (30 percent). The probability of an audit was either 20 percent or 30 percent. The fine on unreported income was either 100 percent (so that the individual paid unpaid taxes plus an additional penalty equal to the amount of unpaid taxes) or 200 percent (or the individual paid unpaid taxes plus a penalty equal to twice the amount of unpaid taxes). Thus there were four different experimental parameter combinations based on the audit probability and penalty. Each parameter combination was held fixed for four rounds before a new combination was presented to subjects; however, our results below hold when we only consider the first four periods, before any subject experienced a new parameter combination. The order of parameters was reversed between sessions. In addition to their earnings from one randomly-selected round, subjects received a fixed participation payment ($10 in the U.S. and €7 in Italy). Experiments lasted about 90 minutes, and payments including participation fee ranged between €13-€22 in Italy (average €17) and between $20 and $35 in the U.S. (average $28).[12]

The main policy variable is the impact of public disclosure versus confidentiality on tax compliance. We consider two very different levels of confidentiality. In a "Full Confidentiality", or baseline, treatment, all information is private: subjects who are audited and found to be noncompliant are assessed a penalty, but none of their compliance information is shared among

[12] We set the income and participation payment levels so that experiment earnings relative to average local student-employment wages were roughly equal across the two countries.

the other subjects. In a second treatment ("Full Disclosure"), subjects who are audited and caught evading are assessed the financial penalty, but their tax-reporting information is no longer kept private. At the end of each round, all participants were shown photos of anyone who was audited and had underreported income. The amount of income reported by each subject was shown with the subject's photo. Because of the picture, we also call this Full Disclosure treatment the "Photo" treatment. A sample screenshot is shown in the bottom of Figure 3.[13]

The experiments were conducted at Georgia State University in the U.S. and at the Università Ca' Foscari Venezia in Italy, using student subjects from each respective institution. In total, 170 subjects participated in the experiment: 92 subjects in the U.S. and 78 subjects in Italy. In each country subjects participated in experimental sessions either with full confidentiality or with full disclosure. In the U.S. 37 subjects participated in sessions with full confidentiality and 55 in sessions with full disclosure; in Italy 38 subjects participated in sessions with full confidentiality and 40 in sessions with full disclosure.

At the end of the experiments the subjects also filled out a demographic survey in order to capture socioeconomic and demographic data of the subject pools in the two countries. The demographic characteristics of our subjects are summarized in Table 1. It is not surprising that there are substantial demographic differences between subjects in the U.S. and Italy. While we follow the standard practice of including demographic controls in our estimation, we do not rule out that demographic differences between the United States and Italy contribute to the cultural differences that may affect tax reporting behavior.

Our theoretical model predicts that compliance will be higher under a higher audit probability and a higher penalty rate. However, our model does not provide a clear a priori expectation of the impact of confidentiality (or culture) on tax compliance. Disclosure of the identity of those who do not fully report income may affect the psychological cost of violating the social norm concerning tax reporting behavior. Disclosure may increase or decrease the cost of violating the social norm, and thus may increase or decrease compliance. Therefore, we rely on the data from this experiment to observe the effect of increased disclosure on tax reporting decisions within and across these two different cultures.

[13] The photos shown in Figure 2 are not those of any subjects in our experiment. All photos were permanently deleted from the camera and computer files immediately after each session.

**Table 1: Subject Characteristics**

| Variable | U.S. | Italy |
|---|---|---|
| Observations | 1472 | 1248 |
| Mean age (in years) | 22.5 | 25.1 |
| Percentage male | 39.1 | 48.7 |
| Mean Family Income ($ or €) | $ 38,070 | € 23,960 |
| Ethnicity (percent of total) | | |
| - White | 4.4 | 96.2 |
| - Black | 75.0 | 2.5 |
| - Asian | 15.2 | - |
| - Other | 4.3 | 1.3 |
| - Prefer not to answer / no answer | 1.1 | - |
| Religion (percent of total) | | |
| - Catholic | 6.5 | 62.8 |
| - Protestant | 10.9 | - |
| - Baptist | 32.6 | - |
| - Muslim | 5.4 | 1.3 |
| - Agnostic/no religion/do not know | 13.1 | 29.4 |
| - Other | 28.2 | 3.9 |
| - Prefer not to answer / no answer | 3.3 | 2.6 |
| Working condition (percent of total) | | |
| - Yes, full employment | 6.5 | 3.9 |
| - Yes, part-time | 37.0 | 18.0 |
| - Yes, self-employed | 1.1 | 10.2 |
| - No | 54.4 | 61.5 |
| - Prefer not to answer / no answer | 1.0 | 6.4 |
| Academic year (percent of total) | | |
| - Freshman | 29.4 | 1.3 |
| - Sophomore | 28.3 | 26.9 |
| - Junior | 22.8 | 20.5 |
| - Senior | 19.6 | 10.3 |
| - Postgraduate | - | 32.0 |
| - Not at university | - | 8.9 |
| - Prefer not to answer / no answer | - | - |
| Marital Status (percent of total) | | |
| - Never married | 97.8 | 85.9 |
| - Married | - | 2.6 |
| - Living together, but not married | - | 5.1 |
| - Divorced | 1.1 | - |
| - Prefer not to answer / no answer | 1.1 | 6.4 |
| Previous participation in an economic experiment (percent of total) | | |
| - Yes | 69.6 | 64.9 |
| - No | 10.9 | 33.3 |
| - Prefer not to answer / no answer | 19.6 | 1.8 |
| Previously filed a tax return? (percent of total) | | |
| - Yes | 38.0 | 15.8 |
| - No | 44.6 | 84.2 |
| - Prefer not to answer / no answer | 17.4 | - |

## 5. Analysis and Results

To distinguish between evasion occurring at the extensive and at the intensive margin, we consider two basic measures of compliance. The first measure is a standard "reporting compliance rate", calculated as the proportion of actual (or "true") income that is reported by each subject in each period. Averaged over all subjects, all rounds, all treatments, and both countries, the mean reporting compliance rate averages 71.3 percent. The second measure is called the "full compliance rate", defined as a binary variable that is equal to 1 if the subject reported fully all income and 0 otherwise. Across all subjects/rounds/treatments/countries, subjects fully reported income 48.2 percent of the time.

### *5.1. Simple Descriptive Evidence*

Table 2 presents summary information on compliance, broken down by enforcement parameters and treatments, including separate calculations for the U.S. and Italy. We provide this general overview of our treatment averages in order to give a sense of the impact of our experiment treatments. However, we emphasize that this summary information is only suggestive. Robust statistical evidence is obtained from regression analyses that are discussed later, where we take account of several possible forms of dependence between observations.

Subjects respond in a predictable manner to changes in the classical enforcement parameters: audit probability and penalty rate. All subjects faced both of these treatments and so we report results from a Wilcoxon test for these comparisons. Pooling across countries and sessions, we observe that an increase in the audit probability from low (*20 percent*) to high (*30 percent*) increases the reporting compliance rate from 66.9 to 75.6 percent ($p \approx 0.0$,), and the full compliance rate from 43.5 to 52.9 percent ($p \approx 0.0$). A similar pattern follows when the penalty rate increases from low (*1x*) to high (*2x*): the reporting compliance rate increases from 66.4 to 76.1 percent ($p \approx 0.0$) and the full compliance rate increases from 43.9 to 52.5 percent ($p \approx 0.0$). Similar increments also hold in the two countries individually, with the actual effects being a bit larger in Italy than in the U.S.

These comparisons are summarized in the following observations:

*Observation 1: An increase in the audit rate increases the reporting compliance rate and the full compliance rate, both in Italy and in the U.S.*

*Observation 2: An increase in the penalty rate increases the reporting compliance rate and the full compliance rate, both in Italy and in the U.S.*

**Table 2: Descriptive Statistics of Compliance**

| | All Decisions | | | U.S. Only | | | Italy Only | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Obs.** | **Reporting Compliance Rate (percent)** | **Full Compliance Rate (percent)** | **Obs.** | **Reporting Compliance Rate (percent)** | **Full Compliance Rate (percent)** | **Obs.** | **Reporting Compliance Rate (percent)** | **Full Compliance Rate (percent)** |
| All Sessions | 2720 | 71.3% | 48.2% | 1472 | 69.0% | 50.6% | 1248 | 73.9% | 45.4% |
| Low Audit | 1360 | 66.9 | 43.5 | 736 | 65.6 | 46.3 | 624 | 68.4 | 40.1 |
| High Audit | 1360 | 75.6 | 52.9 | 736 | 72.5 | 54.9 | 624 | 79.4 | 50.6 |
| Low Penalty | 1360 | 66.4 | 43.9 | 736 | 66.3 | 48.0 | 624 | 66.6 | 39.1 |
| High Penalty | 1360 | 76.1 | 52.5 | 736 | 71.8 | 53.3 | 624 | 81.2 | 51.6 |
| Baseline - Full Confidentiality | 1200 | 69.0 | 37.7 | 592 | 64.8 | 38.2 | 608 | 73.1 | 37.1 |
| Full Disclosure (photos) | 1520 | 73.1 | 56.5 | 880 | 71.9 | 58.9 | 640 | 74.7 | 53.1 |

Our main interest is the effect of changes in the level of confidentiality on compliance, as well as the extent to which compliance behavior differs across countries. Because both confidentiality and culture vary across subjects, we use a Mann-Whitney U test for all remaining comparisons.

The average reporting compliance rate across all subjects/rounds/countries without photos is 69.0 percent. In sessions where photos are shown, the average reporting compliance rate rises to 73.1 percent ($p \approx 0.0029$). If we examine instead the binary measure of compliance, the effect of photos appears even more dramatic: the full compliance rate is 37.7 percent in the baseline condition compared with 56.5 percent in sessions with photos ($p \approx 0$). The results in the two countries are consistent, even if the effects in Italy appear a bit weaker than in the U.S. The reporting compliance rate increases in the U.S. between the baseline and the photo treatment by 7.2 percent ($p \approx 0.0005$), and the full compliance rate increases by 20.8 percent ($p \approx 0$). In Italy the corresponding increases between baseline and photos treatment are 1.6 percent (positive but not significant, $p \approx 0.2146$) and 16.0 percent ($p \approx 0$), respectively.

These results are summarized in the following observations:

*Observation 3: Showing photos increases the reporting compliance rate and the full compliance rate, both in Italy and in the U.S.*

*Observation 4: Showing photos has a larger effect on the reporting compliance rate and the full compliance rate in the U.S. than in Italy.*

Observation 4 is in line with the notion that underreporting is more socially accepted in Italy than in the U.S. Accordingly, changing the level of confidentiality has a larger effect in the U.S. than in Italy. At the same time, the overall reporting compliance rate is generally higher in Italy than in the U.S., particularly in the baseline treatment (73.1 percent versus 64.9 percent, $p=0.0001$) and to some extent in treatments with photos (74.7 percent in Italy versus 71.9 percent in the U.S., $p=0.0903$). Given that Italy is often regarded as a country where evasion is widespread, the latter evidence may seem surprising. However, Andrighetto et al. (2016) offer a result from their experimental study of tax compliance in Sweden and Italy. They find that cheating occurs in both countries but the Italians are more likely to “fudge” (engage in partial reporting) than be completely dishonest. While the root of fudging is not investigated in Andrighetto et al., the authors note that fudging versus outright evasion may be more difficult to address due to the haziness of the evasion act. Fudging may be seen by some as “not cheating” thus making the social norm more flexible.

The evidence from Table 2 lends support to this idea. In the baseline treatment, the full compliance rate is higher in the U.S. than in Italy even if by a small amount (38.2 percent versus 37.1 percent); in the photos treatment, the difference becomes larger, 59.0 percent in the U.S. versus 53.1 per cent in Italy ($p \approx 0.0115$). This statistically significant effect from the photo treatment is stronger in the U.S. than in Italy, which supports the following observation:

*Observation 5: The full compliance rate is higher in the U.S. than in Italy, particularly in the photo treatment.*

Figures 4 and 5 provide further supporting evidence for Observation 5. Figure 4 reports the cumulative distribution function (CDF) of the “evasion rate” (defined as 1 minus the reporting compliance rate) under the different parameters for the audit probability and the penalty, pooling across countries but distinguishing between sessions with photos and without photos. (The results for the individual countries are similar.) The CDFs of the photo treatment show that high audit probabilities and high penalty rates are characterized by almost parallel right-shifts of the corresponding CDF with low parameters for both variables, indicating that the traditional enforcement parameters have similar effects on the evasion rates at all evasion levels. Particularly, the rise in compliance due to the increase in each parameter occurs similarly at the extensive and intensive margins. The same qualitative effects occur in treatments with and without photos, even if in the former case the effect of increasing the audit probability is clearly smaller than in the baseline. This result may be due to nonlinear and decreasing effects of the audit probability on compliance; that is, given that in treatments with photos compliance is already higher than in the baseline treatment, the marginal effect of increasing the audit probability is higher in the baseline treatment than in the treatment with photos.

Figure 5 compares the CDFs of the evasion rates for treatments with photos and without photos for the aggregate of the two countries and separately for Italy and for the U.S. The CDFs in Figure 5 suggest very different effects than for the classical enforcement parameters in Figure 4. For both Italy and the U.S., the CDFs with photos remain higher than those without photos for small evasion rates, but the effects become progressively smaller for medium and high evasion rates, tending to disappear and possibly even reversing in Italy for very high evasion rates.

**Figure 4: Cumulative Distributions of Evasion Rates by Enforcement Parameters**

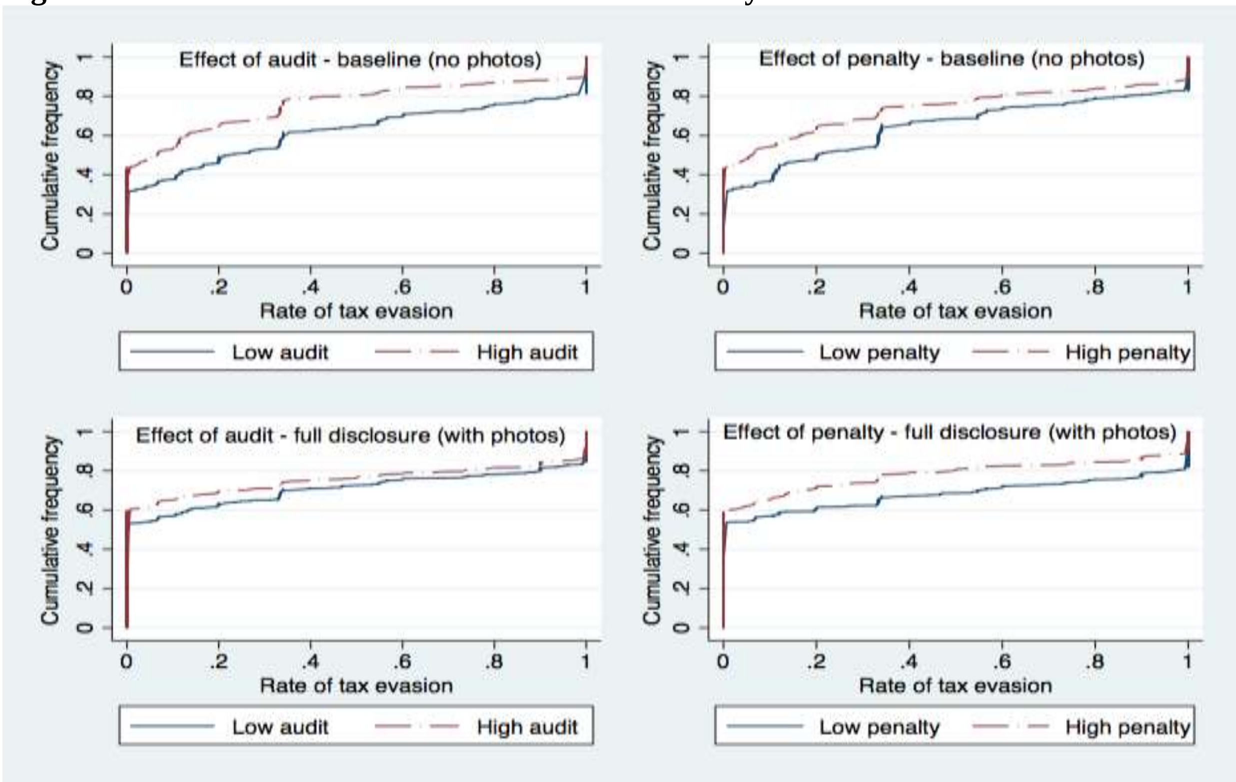
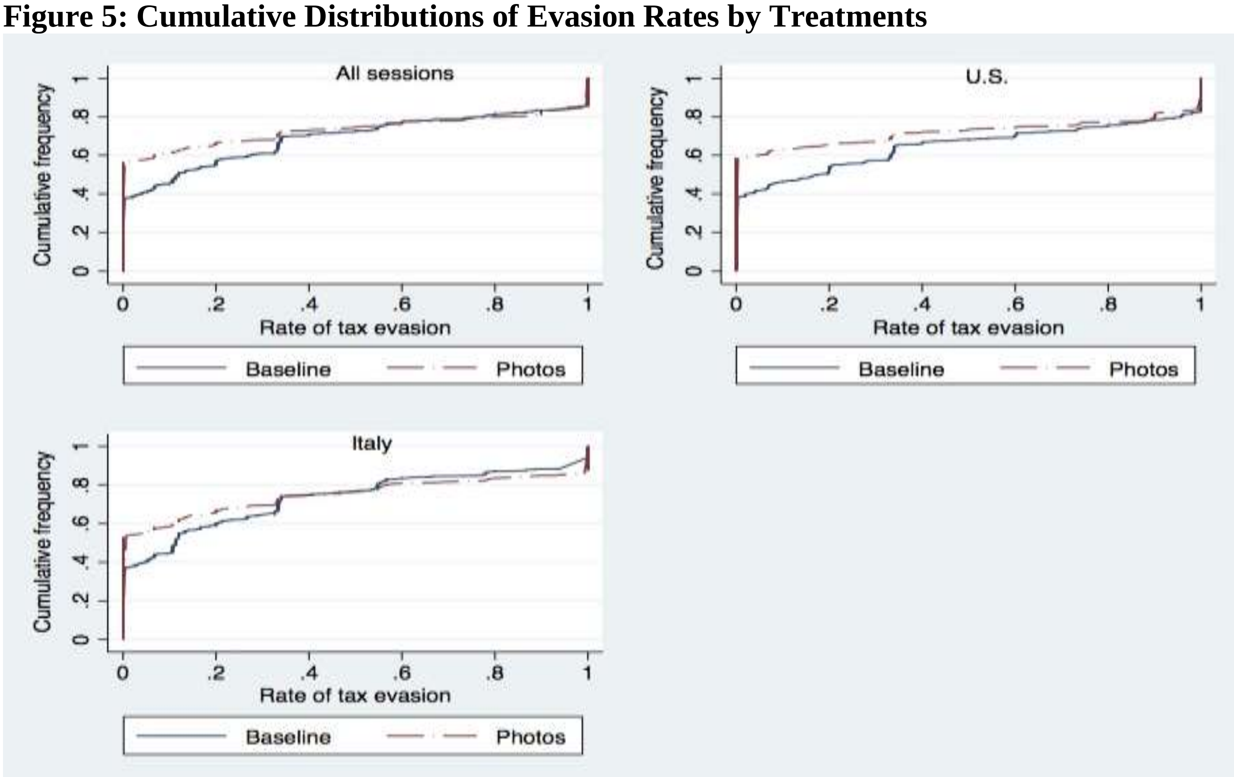



**Figure 5: Cumulative Distributions of Evasion Rates by Treatments**



The evidence from the CDFs of Figures 4 and 5 suggests the following observations:

*Observation 6: Both in the baseline treatment and in the photo treatment, the effect of traditional enforcement parameters occurs both at the intensive and extensive margin. In the photo treatment, the effect of traditional enforcement parameters is smaller than in the baseline treatment.*

*Observation 7: Both in Italy and in the U.S., the effect of photos is mainly at the extensive margin, and is concentrated in the lower tail of the distribution of the evasion rates.*

Finally, note that the different impacts of photos at the extensive and intensive margins increase the distance between the incomes of those who evade and those who do not evade. In fact, the ratio of the average income of tax evaders to that of full compliers decreases between the baseline and the photo treatment from 0.43 to 0.31 in the U.S. and from 0.57 to 0.46 in Italy.

*5.2. Regression Analysis*

The observations from simple descriptive statistics are suggestive, but the results need to be fully examined by appropriate econometric techniques. We start with Table 3, which presents the results of 4 models for the determinants of subjects' compliance behavior. The first two models (1) and (2) are estimation results from a pooled (or population-averaged) tobit regression and from a panel tobit regression with random effects, respectively. Censored tobit models are commonly adopted in this kind of analysis in which evasion can be chosen between zero and the whole subject's income (inclusively).[14] The models are specified as:

$$ER^{*}_{it} = \boldsymbol{x'_{it}\beta} + \alpha_i + \varepsilon_{it} \,, \tag{5}$$

where the dependent variable $ER^{*}_{it}$ is the latent "evasion rate" (again calculated as [1- reporting compliance rate]) of subject $i$ in period $t$, and where the observed evasion rate $ER_{i,t}$ is given by:

$$ER_{it} = \begin{cases} 0 \;\; if \;\; ER^{*}_{it} \leq 0 \\ ER^{*}_{it} \; if \; 0 < \; ER^{*}_{it} < 1 \\ 1 \;\; if \;\; ER^{*}_{it} \geq 1 \end{cases} \tag{6}$$

The regressor vector $\boldsymbol{x_{i,t}}$ includes four dummies for the treatments and parameters of the experiment, an intercept, and a variable for *Period*. The four dummies are: a dummy variable for *Photo*, equal to 1 in treatments with photos and 0 in the baseline; a dummy variable for *Low Audit*, equal to 1 if the audit probability is low and 0 otherwise; a dummy variable for *Low Penalty*, equal to 1 if the penalty rate is low and 0 otherwise; and a dummy variable for *Italy,*

[14] Alternatively, a probit model could be estimated, with the dependent variable equal to 1 for positive evasion and 0 otherwise. In this case the use of a binary dependent variable is taken as a general compliance measure, rather than as an altogether specific step in the decision to comply or not, as in the different approach that we follow.

**Table 3: Effects of Treatment Variables on Choices – Censored Regressions and Double-hurdle Models**

| | Censored regressions | | Double-hurdle (DH) regressions | | | |
|---|---|---|---|---|---|---|
| | Model (1) | Model (2) | Model (3) | | Model (4) | |
| | | | Pooled DH | | Panel DH with random effects | |
| Variable | Pooled tobit | Panel tobit with random effects | First Hurdle | Second Hurdle | First Hurdle | Second Hurdle |
| Photos | - 0.213*** (0.038) | - 0.301*** (0.112) | - 0.858*** (0.094) | 0.158*** (0.029) | - 1.043*** (0.351) | 0.044 (0.064) |
| Low Audit | 0.242*** (0.038) | 0.233*** (0.030) | 0.126* (0.075) | 0.147*** (0.028) | - 0.273 (0.355) | 0.177*** (0.022) |
| Low Penalty | 0.230*** (0.037) | 0.238*** (0.029) | 0.054 (0.074) | 0.170*** (0.028) | | 0.177*** (0.021) |
| Italy | - 0.059 (0.037) | - 0.025 (0.112) | 0.411*** (0.083) | - 0.214*** (0.028) | 0.260 (0.261) | - 0.123** (0.058) |
| Period | 0.012*** (0.004) | 0.012*** (0.003) | - 0.014 (0.009) | 0.014*** (0.003) | | 0.008*** (0.002) |
| Constant | - 0.179*** (0.059) | - 0.208* (0.107) | 0.748*** (0.143) | 0.153*** (0.044) | 1.628*** (0.341) | 0.032 (0.058) |
| $\sigma_\alpha$ | | 0.687 (0.050) | | 0.440 (0.013) | | 0.328 (0.026) |
| $\sigma_\varepsilon$ | 0.859 (0.023) | 0.622 (0.016) | | 0.440 (0.013) | | 0.467 (0.010) |
| Transformed $\rho$ | | | | | | -0.442 (0.440) |
| $\chi^2$ (Prob > $\chi^2$) | 115.44 (0.000) | 136.63 (0.000) | 283.383 (0.000) | 204.447 (0.000) | 81.477 (0.000) | 144.810 (0.000) |
| $\chi^2$ overall (Prob > $\chi^2$) | | | 299.042 (0.000) | | 153.741 (0.000) | |
| Log likelihood | -2613.774 | -2147.039 | -2166.450 | | -1739.645 | |
| Observations | 2720 | 2720 | 2720 | | 2720 | |

Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

equal to 1 for sessions run in Italy and 0 otherwise. The error term $\varepsilon_{it}$ is the contemporaneous idiosyncratic error term, assumed to be normally distributed with zero mean and variance $\sigma_\varepsilon^2$. The $\alpha_i$ variables are the random effects that control for unobservable individual characteristics, also assumed to be normally distributed with zero mean and variance $\sigma_\alpha^2$. In the pooled (or population-averaged) model (1), these effects $\alpha_i$ are assumed equal to 0, so that the model ignores between-subject heterogeneity with the likely correlation of the errors for a given individual over periods.

The results obtained by the two tobit models are qualitative similar (Table 3). Showing photos of those caught evading has a negative effect on evasion. Setting a low audit probability and a low penalty increase evasion relative to a high audit probability and a high penalty rate. The dummy for Italy does not indicate any statistical significance of country, whereas the coefficient on the period variable indicates a moderate tendency of the evasion rate to increase with repeated periods. Residual analysis in the panel tobit shows the importance of between-subject heterogeneity (or the individual-specific random effects $\alpha_i$), which contribute to more than 50 percent of the total variance (or $\sigma_\alpha^2/(\sigma_\alpha^2+\sigma_\varepsilon^2)=0.55$).

We also compute the marginal effects on evasion behavior with respect to changes in the regressors. The effect of *Photos* in the panel tobit reduces the evasion rate $ER^*_{it}$ among subjects not at a boundary (e.g., full evasion or no evasion) by -10.3 percent; the effect is +8.1 percent for *Low Audit* and +8.2 percent for *Low Penalty*), with the marginal effect on the probability of being uncensored equal to -5.7 percent.

The standard assumption of the censored tobit regression model, or that the variables affecting the decision to evade taxes have the same effect on whether a person evades and (conditional on evasion) an individual's level of evasion, may not be appropriate in this environment. In fact, observed behavior in our experiment cause us to be skeptical of this assumption. The CDFs shown in Figure 5 and the related Observation 7 suggest that reducing confidentiality has a differential effect on the proportion of choices that involve reporting income fully compared with the amount of income that is reported. More generally, the fixed ethical and social costs of evasion featured in our model imply that there may be factors affecting tax evasion decisions at the extensive margin that do not have the same effect at the intensive margin.

While the tobit model is used in most studies because of potential censoring, it cannot distinguish between compliance on extensive and intensive margins. A different estimation strategy is required to disentangle these two aspects of compliance: *whether* a subject evades and *how much* one evades (for those not fully compliant). To examine this, we use a two-part or double-hurdle (DH) model, introduced by Cragg (1971) in his study of the demand for durables. This model allows us to estimate the two distinct processes underlying the decision to evade: the first hurdle, interpretable as a probit model, determines whether or not a person participates in evasion and is particularly suited to capture effect occurring mainly at the extensive margin; the second hurdle, interpretable as a tobit model, determines the level of evasion only for those people who ever choose to evade and is therefore relevant for the effect occurring at the intensive margin.

Models (3) and (4) in Table 3 report estimates of the DH regressions: a pooled DH in model (3) and a panel DH with random effects in model (4). These models are estimated using the double-hurdle procedure specifically developed by Engel and Moffat (2014) for economic experiments.

In the pooled DH model, the observed evasion rate $ER_{it}$ of subject $i$ in period $t$ is assumed to be given by:

(7) $ER_{it} = d_{it} ER^{*}_{it}$ ,

where $d_{it}$ is a binary variable for evasion equal to 1 if $d^{*}_{it} > 0$ and 0 otherwise and where $ER^{*}_{\mathrm{it}} = max\{ER^{**}_{it}, 0\}$. The two latent variables $d^{*}_{it}$ and $ER^{**}_{it}$ are specified in the first and second hurdle, respectively. The first hurdle is given by:

(8) $d^{*}_{it} = \boldsymbol{z'_{it}\gamma} + \varepsilon_{1,it}$ ,

where $\varepsilon_{1,it}$ is subject $i$'s idiosyncratic propensity to pass the hurdle in period $t$, assumed normally distributed with zero mean and variance normalized to unity, a standard assumption in probit estimation to allow for identification. The second hurdle is given by:

(9) $ER^{**}_{\mathrm{it}} = \boldsymbol{x'_{it}\beta} + \alpha_i + \varepsilon_{2,it}$ .

As in the tobit regression, the pooled DH model includes only the contemporaneous error term $\varepsilon_{2,it}$ (with normal distribution, zero mean and variance $\sigma_{\varepsilon}^{2}$), and the subject-specific random effects $\alpha_i$ are assumed equal to 0. Moreover, in the pooled DH the two errors $\varepsilon_{1,it}$ and $\varepsilon_{2,it}$ are assumed independently distributed.

The panel DH model includes the subject-specific random effects $\alpha_i$ (normally distributed with zero mean and variance $\sigma_{\alpha}^{2}$), which measure subject $i$'s idiosyncratic propensity to evade, conditional on passing the first hurdle. The panel DH therefore allows for possible correlation between the two hurdles, which goes precisely through the random effects $\alpha_i$ and the errors $\varepsilon_{1,i}$ of the first hurdle via the correlation between the random effects and the errors, or $\rho = corr\ (\alpha, \varepsilon_1)$.

The panel DH model has one characteristic that makes it very different from all other models estimated in Table 3: "…that the first hurdle has only one outcome per subject and that outcome applies to all observations for that subject" (Engel and Moffat, 2014). This formally implies that in equation (7) of the panel DH model $d_{it}=d_i$ for all $t=1,...T$, so that in equation (8) the subscript for time $t$ must be suppressed. In practice, this means that a subject is classified as a "0-type" subject (so that the individual has 0 evasion), only if the subject fully reports his or her income in all periods of the experiment. Otherwise, the subject is identified as a potential evader. So, an individual who fully complies in some (but not all) rounds of the experiment would be a potential evader, as would someone who evades in some or all rounds. This is obviously a very important identifying restriction of the model, implying that, if there are indeed 0-type (fully compliant) subjects in the experiment and if they are correctly determined, then the estimation of a panel DH model can significantly improve the whole fit. We believe both the pooled and random effects DH models capture different but important characteristics of our data, and so we report results from both models.

The results of the two DH regressions are shown in Table 3. Results from estimating the first and second hurdle equations are shown in separate columns under each model. Results from the first hurdle provide insight into how the regressors affect the probability that one is identified as a potential evader. The second hurdle addresses their effect on the amount of evasion engaged in by potential evaders. Results from models (3) and (4) offer additional insight into how our treatments affect compliance. The DH models confirm the general results found from the Tobit estimation, but they also reveal that the variables in our model have different impacts in the two hurdles.

Consider the effect of showing photos of those found to have underreported income. In the pooled DH model (3), the effect of *Photos* is very large and negative in the first hurdle; however, its effect is positive in the second hurdle. In other words, the effect of the *Photos* treatment is to reduce the probability of a subject being a potential evader, but to increase the level of evasion for those who are classified as evaders. This is consistent with the notion that photos increase the fixed cost of evasion (making subjects less likely to ever evade), but that subjects who pass this hurdle evade more than they would otherwise. The effect of the dummy variable for Italy is also different in the two hurdles: it is positive in the first hurdle and negative in the second. This is consistent with the notion that subjects in Italy are more likely to evade than those in the U.S., but among those classified as potential evaders, Italians evade by a lesser amount.

The estimates for the panel DH model (4) are similar to those from the pooled DH model (3), although the effects are not always as sharp as in the pooled DH.[15] Nevertheless, the overall fit is better in the panel DH than in the pooled DH (as indicated by the log likelihood of the panel DH model and the values of $\sigma_\alpha$ and $\sigma_\varepsilon$; see Table 3).[16] In particular, the panel DH model (4) confirms that the negative impact of *Photos* on evasion is because it reduces the propensity to evade (shown in the first hurdle), while the impacts of the other variables are primarily on the extent of evasion (shown in the second hurdle). As observed in the pooled DH model (3), the negative effect on evasion from showing photos is largely due to subjects who switch from some level of evasion to fully reporting their income. This is consistent with the inclusion of fixed costs of cheating in our model In fact, when computing the marginal effects for the panel DH of model (4), we find that the probability of passing the first hurdle in the treatment with photos decreases by almost 25 percent relative to the baseline treatment. On the other hand, the marginal effect of *Photos* in the second hurdle on the latent tax evasion rate (which in the earlier tobit estimation was estimated at -10 percent) is now virtually zero. The marginal effects of the other regressors in the second hurdle become +6.7 percent for both *Low Audit* and *Low Penalty* (both are lower than in the tobit estimation), while the effect of the *Italy* dummy is -4.7 percent (which is not significant in the tobit estimation). Finally, note that the constant term in the first hurdle confirms the presence of subjects who report zero income (an estimated 5.2 percent of the sample).[17]

The results shown in Table 3 confirm most of the descriptive observations from the previous section. While neither the pooled nor the panel model is a perfect indicator for

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[15] The regressors in the first hurdle of the panel DH do not include the variable *Period* (because the model has only one outcome per subject) and the variable *Low Penalty* (for reasons of convergence). The results of the pooled DH regression (estimated also by sampling from participants as clusters using bootstrapping) show that the variable can be safely omitted from the first hurdle.

[16] As previously indicated, the pooled DH model (3) treats observations as if they were independent, ignoring not only potential within subject-correlation but also failing to fully identify subjects rather than observations to be of 0-type. This may also imply that some censored zero observations are misinterpreted as 0-type observations, with the consequence of exaggerating the opposite effect of some regressors in the two hurdles.

[17] We have checked for statistical significance of the double-hurdle in the baseline treatment (which in case of the intercept alone reduces to a p-tobit panel model) by conducting a likelihood ratio test to compare it with a standard censored panel tobit. Further, note that the transformed ρ is not significant (e.g., the error terms are uncorrelated), suggesting a bootstrap technique is not necessary.

**Table 4: Panel Double-hurdle with Random Effects Models – Interaction Effects**

| | Panel double-hurdle with random effects | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model (5) | | Model (6) | | Model (7) | | Model (8) | |
| Variable | First Hurdle | Second Hurdle | First Hurdle | Second Hurdle | First Hurdle | Second Hurdle | First Hurdle | Second Hurdle |
| Photos | - 0.920*** (0.296) | 0.051 (0.065) | -1.049*** (0.316) | 0.051 (0.083) | -1.052*** (0.314) | 0.098 (0.085) | -1.299*** (0.408) | - 0.153* (0.092) |
| Low Audit | | 0.117*** (0.022) | | 0.177*** (0.022) | | 0.223*** (0.030) | | 0.223*** (0.030) |
| Low Penalty | | 0.177*** (0.022) | | 0.177*** (0.021) | | 0.177*** (0.021) | | 0.177*** (0.021) |
| Italy | | - 0.109* (0.056) | | - 0.114 (0.080) | | - 0.115 (0.080) | | - 0.121 (0.080) |
| Italy * Photos | | | 0.306 (0.293) | - 0.012 (0.115) | 0.479 (0.331) | - 0.013 (0.115) | 0.414 (0.340) | 0.054 (0.107) |
| Low Audit * Photos | | | | | - 0.686 (0.518) | - 0.096** (0.042) | - 0.627 (0.531) | - 0.096** (0.042) |
| Male | | | | | | | -0.099 (0.496) | 0.018 (0.082) |
| Male * Photos | | | | | | | 0.560 (0.582) | 0.227** (0.108) |
| Period | | 0.008*** (0.002) | | 0.008*** (0.002) | | 0.007*** (0.002) | | 0.007*** (0.002) |
| Constant | 1.585*** (0.256) | 0.029 (0.057) | 1.592*** (0.255) | 0.030 (0.063) | 1.595*** (0.253) | 0.014 (0.063) | 1.692*** (0.350) | - 0.018 (0.069) |
| $\sigma_\alpha$ | | 0.330 (0.028) | | 0.329 (0.026) | | 0.329 (0.026) | | 0.319 (0.025) |
| $\sigma_\varepsilon$ | | 0.467 (0.010) | | 0.467 (0.010) | | 0.466 (0.010) | | 0.465 (0.010) |
| Transformed $\rho$ | | - 0.528 (0.469) | | - 0.481 (0.432) | | - 0.457 (0.411) | | 0.468 (0.366)) |
| $\chi^2$ (Prob > $\chi^2$) | 9.678 (0.001) | 143.613 (0.000) | 11.060 (0.011) | 144.595 (0.000) | 17.866 (0.003) | 151.346 (0.000) | 31.801 (0.002) | 162.380 (0.000) |
| $\chi^2$ overall (Prob > $\chi^2$) | 152.864 (0.000) | | 154.460 (0.000) | | 161.437 (0.000) | | 173.826 (0.000) | |
| Log likelihood | -1740.363 | | -1739.809 | | -1736.457 | | -1731.203 | |
| Observations | 2720 | | 2720 | | 2720 | | 2720 | |

Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1

**Table 5: Panel Double-hurdle Models – Robustness Checks**

| | Panel double-hurdle with random effects | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Model (9) | | Model (10) | | Model (11) | | Model (12) | |
| | Period 1-16 | | Period 1-8 | | Period 9-16 | | Period 2-16 | |
| Variable | First Hurdle | Second Hurdle | First Hurdle | Second Hurdle | First Hurdle | Second Hurdle | First Hurdle | Second Hurdle |
| Photos | - 1.081*** (0.306) | - 0.121* (0.074) | -0.968*** (0.297) | - 0.193* (0.081) | - 0.931*** (0.291) | 0.022 (0.100) | -1.425*** (0.346) | - 0.076 (0.080) |
| Low Audit | | 0.223*** (0.030) | | 0.165*** (0.040) | | 0.292*** (0.043) | | 0.229*** (0.031) |
| Low Penalty | | 0.177*** (0.021) | | 0.043 (0.063) | | 0.100 (0.066) | | 0.157*** (0.022) |
| Italy | | - 0.090* (0.053) | | - 0.061 (0.057) | | - 0.133** (0.065) | | - 0.084 (0.053) |
| Italy * Photos | 0.466 (0.337) | | 0.654* (0.372) | | 0.458 (0.335) | | 0.593* (0.349) | |
| Low Audit * Photos | - 0.701 (0.533) | - 0.096** (0.043) | - 0.792 (0.567) | - 0.033 (0.064) | - 0.527 (0.552) | - 0.152** (0.068) | - 0.459 (0.554) | - 0.101** (0.044) |
| Male * Photos | | 0.229*** (0.070) | | 0.203** (0.0.80) | | 0.197** (0.093) | | 0.216*** (0.074) |
| Period | | 0.007*** (0.002) | | 0.042*** (0.013) | | - 0.009 (0.013) | | 0.004*** (0.003) |
| Identified Last Period | | | | | | | 5.467 (263.241) | 0.020 (0.046) |
| Others Identified Last Period (%) | | | | | | | 5.637 (3.742) | - 0.164 (0.267) |
| Constant | 1.642*** (0.247) | - 0.022 (0.056) | 1.458*** (0.232) | -0.043 (0.071) | 1.340*** (0.230) | 0.096 (0.112) | 1.630*** (0.249) | 0.031 (0.060) |
| $\sigma_\alpha$ | | 0.314 (0.023) | | 0.282 (0.030) | | 0.319 (0.033) | | 0.309 (0.021) |
| $\sigma_\varepsilon$ | | 0.465 (0.010) | | 0.447 (0.014) | | 0.464 (0.014) | | 0.465 (0.010) |
| Transformed $\rho$ | | 0.334 (0.331) | | 0.363 (0.505) | | 0.324 (0.472) | | - 0.060 (0.363) |
| $\chi^2$ (Prob > $\chi^2$) | 19.364 (0.001) | 159.145 (0.000) | 12.866 (0.012) | 70.134 (0.000) | 16.199 (0.003) | 108.672 (0.000) | 24.233 (0.002) | 137.237 (0.000) |
| $\chi^2$ overall (Prob > $\chi^2$) | 171.931 (0.000) | | 81.691 (0.000) | | 119.893 (0.000) | | 152.031 (0.000) | |
| Log likelihood | -1732.502 | | - 886.196 | | - 907.624 | | -1635.151 | |
| Observations | 2720 | | 1360 | | 1360 | | 2550 | |

Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

estimation purposes, their countervailing strengths and weakness yield estimates that likely encompass the true marginal effects of tax arrears disclosure. Nevertheless, there are other factors that need to be considered. Tables 4 and 5 present additional regressions that add complexity to the panel DH model. Models (6) and (7), shown in Table 4, respectively, add interaction terms *Italy*Photos* and *Low Audit *Photos*. We see that the dummy for Italy interacted with photos in the first hurdle shows a positive coefficient, as expected from Observation 6, although the coefficient is not statistically significant, possibly because of the difficulty of estimating the effect with precision given the size of the sample and the length of the panel. In the second hurdle, the dummy for *Low Audit* interacted with the dummy for *Photos* confirms the evidence from the CDFs of Figure 4, namely that in the treatment with photos, an increase in the audit probability has a smaller impact on compliance than in the baseline.

Model (8) adds gender to the variables in our model (see Table 4). In the first hurdle there are no statistically significant gender effects, so that males and females do not behave differently in the binary choice of whether to engage in tax evasion. Considered on its own, gender also has no significant effect on the level of evasion in the second hurdle model. However, the interaction variable in the second hurdle shows that, in the photos treatment, females evade less than males.[18] We have also examined the effect of other demographic and social controls, including a variable indicating the subject's reported religion. We find no significant effect of religion. Including a dummy variable for those who report they are Catholic instead of the dummy variable for the sessions conducted in Italy produces essentially the same estimates reported in model (8).

Finally, we further test the robustness of our panel estimation results in Table 5. Models (9), (10), and (11) compare the full sample to the first 8 periods and last 8 periods of the experiment. Comparing these models seems particularly relevant as a robustness check for the estimates of the first hurdle, which has only one outcome per subject applying to all observations for that subject. Accordingly, it is important to see whether the results change when we modify the number of observations that apply to each subject. The estimates in models (9), (10), and (11) indicate that the effects of the variables, in particular the effect of *Photos* in the first hurdle, are indeed stable over the whole sample and on the two sub-periods. In model (12), we test for the

[18] We do not know the specific reasons for this gender difference. However, this result is similar to recent findings that women cheat less on taxes than men (D'Attoma et al., forthcoming), who suggest that gender differences in behavior toward evasion persist even after controlling for a number of environmental factors.

effect of being audited in the previous round and for the proportion of how many others are identified with photos. We find that neither variable has an effect on compliance. Other (unreported) estimations confirm the robustness of our results.

Consistent across all of the DH models we tested is the impact of disclosure on evasion: showing photos of those who underreported income has a significant, negative effect on the decision of whether to evade, but in most specifications it has no significant effect on the extent of evasion for those who evade. In contrast, our other variables of interest (audit probability, penalty rate, and other socio-demographic control variables) have no significant effect on the decision to evade, but do affect the extent of the evasion. Considered in the context of our theoretical model, this suggests that shame has the effect of increasing the fixed costs of evasion in a way that other factors in our model do not.

## 6. Conclusions

How will individuals react to the public disclosure of their tax evasion? Will they treat public shame as an additional cost of cheating and respond by increasing their compliance? Or will the threat of public shame crowd out an individual's intrinsic motivation to obey the law and reduce compliance as a retaliatory action against an intrusive government?

This paper uses laboratory methods to examine the impact of disclosure on tax compliance, comparing subject responses in Italy and the U.S. Our results support the notion that public shame is an additional deterrent to tax evaders, beyond the traditional enforcement tools of higher audit and enhanced penalty rates. However, while traditional instruments work primarily on the intensive margin, we find that the deterrent effect of public shame works mainly through stopping people from engaging in evasion activity, or the extensive margin. Displaying photos of those found to have underreported income has a significant, negative effect on the likelihood of engaging in any level of evasion. This is consistent with the notion that people experience a utility loss by violating compliance norms, and this loss increases when the violation is known publicly. No other demographic or social control variables have a significant effect on probability of non-compliance. We also find that the deterrent effect of public shame is qualitatively similar in the U.S. and Italy, despite differences in the compliance norms across the two countries. [19]

[19] As suggested by an anonymous referee, an intriguing possibility is to use our experimental data to estimate the

Finally, one implication of our results is that, since public disclosure affects mainly the decision to participate in tax evasion, it also increases the income disparity between those who fully comply with tax law and those who make large evasion decisions. This undesired effect of public disclosure could be remedied in policies conducted in the field by targeting audits on people more disposed to tax evasion and by increasing financial penalties for large tax evaders.

Thus, while deterrence via audits and fines remain basic elements of any sustained government policy to improve compliance, our results suggest that public disclosure of tax evaders can represent an additional – and strategically powerful – instrument.

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magnitude of the two psychological cost components. We leave this issue to future research.

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## APPENDIX A: MATHEMATICAL MODEL

The taxpayer's utility function is *U(I;C)*. The agent chooses $D$ to maximize equation (4) from the text:

$$EU(D; C) = pU(I_c;\ C) + (1-p)U(I_N\ ; C) \qquad (4)$$

where $I_C = I - tD - f[t(I-D)]$, $I_N = I - tD$, $C =\ \gamma E + K$, with $E = I - D, \gamma > 0, K = 0$ whenever $E = 0$ and $K > 0$ whenever $E > 0$. We assume that utility is increasing and concave in the first argument, so that $U_I$>0 (or the first partial derivative on income is positive) and $U_{II}$<0 (or the second partial derivative on income is negative). We also assume that utility is decreasing and concave in the second ($U_C$<0 and $U_{CC}$<0).

The first-order condition for an internal solution is:

$$\frac{\partial EU(D;C)}{\partial D} =\ p[t(f-1)U_I(I_C;C) - \gamma U_C(I_C;C)] + (1-p)[(-t)U_I(I_N;C) - \gamma U_C(I_N;C)] = 0 \quad (5)$$

We assume that $\frac{\partial^2 EU}{\partial D \partial D} < 0$ for $0 \leq D \leq I$, so that the second-order condition is always satisfied at an internal solution.

When $C =\ \gamma E$, so that $C$ includes only the variable cost, a necessary and sufficient condition for $E > 0$ is that:

$$\frac{\partial EU(I;0)}{\partial D} = (pf-1)U_I(I;0) - \gamma U_C(I;0) < 0 \quad (6)$$

The condition for positive reporting $D > 0$ is $\frac{\partial EU(0;\ C)}{\partial D} > 0$. In the absence of a variable psychological cost, condition (6) for $E > 0$ turns into the standard condition of Allingham-Sandmo (1972), or:

$$\frac{\partial EU(I;0)}{\partial D} = (pf-1) < 0 \quad (7)$$

Thus, with a variable psychological cost the taxpayer may remain at $E = 0$ even when $(1 - pf) > 0$, as long as $(1-pf)U_I(I;0) < -\gamma U_C(I;0)$. This condition is similar to Gordon (1984) even if there the utility function takes the simpler form $U(I;C) = U(I) - vE$, so that $-\gamma U_2(I;0) = v$.

When $C = K$, so that $C$ includes only the fixed cost, the first-order condition simplifies to:

$$\frac{\partial EU(D;K)}{\partial D} =\ p[t(f-1)U_I(I_C;K)] + (1-p)[(-t)U_I(I_N;K)] = 0 \quad (8)$$

Condition $\frac{\partial EU(I;\,0)}{\partial D} < 0$ is now necessary but not sufficient for $E > 0$. This is because, given $U_C < 0$, the taxpayer's utility at $E = 0$ is always greater than the utility very close to $I$, namely:

$$U(I;0) > \lim_{D^{+}\to I} EU(D;K) \qquad (9)$$

Thus, with fixed costs the value $D^* < I$ that solves the first-order condition $\frac{\partial EU(D^*;\,C)}{\partial D} = 0$ (or such that $D^* = 0$ when $\frac{\partial EU(0;\,C)}{\partial D} > 0$) can be a local maximum. For a global maximum, it is necessary to compare $EU(D^*;K)$ with the taxpayer's utility at certainty: the taxpayer chooses $D^* < I$ when $EU(D^*;K) > U(I;0)$ and chooses $D^* = I$ (or $E = 0$) when $EU(D^*;K) < U(I;0)$.

The taxpayer's problem can be analyzed diagrammatically. Panels A and B in Figure 1 of the text shows the taxpayer's indifference maps in the $(I_C, I_N) - plane$ for fixed values of $\bar{C}$. For example, the indifference curve labeled $U(\cdot;\ 0)$ has been derived in the diagrams of both panels for $C = 0$. This curve is useful for the sake of comparison, as it represents the indifference curve of the Allingham and Sandmo (1972) model, in the absence of psychological costs.

The slope of an indifference curve at any point $(I_C, I_N)$ is, for fixed $\bar{C}$, derived by totally differentiating equation (4) at $\bar{C}$ and computing $\frac{dI_C}{dI_N}(\bar{C})\Big|_{dEU=0}$. We obtain:

$$\left.\frac{dI_C}{dI_N}\right|_{dEU=0} = -\frac{(1-p)}{p}\frac{U_I(;,\bar{C})}{U_I(I_C;\bar{C})} \quad (10)$$

The effect on the slope of a change in $\bar{C}$ is given by:

$$\frac{\partial\left(\left.\frac{dI_C}{dI_N}\right|_{dEU=0}\right)}{\partial\bar{C}} = -\frac{(1-p)}{p\left[U_I(I_C;\bar{C})\right]^2}\left[U_{IC}(I_N;\bar{C})U_I(I_C;\bar{C}) - U_{IC}(I_C;\bar{C})U_I(I_N;\bar{C})\right] \quad (11)$$

The sign of this derivative is ambiguous. However, it makes sense to assume that the overall effect is non-negative, which requires that the square-bracket of equation (11) is non-positive, or:

$$[U_{IC}(I_N;C)U_I(I_C;C) - U_{IC}(I_C;C)U_I(I_N;C)] \leq 0 \quad (12)$$

In particular, when condition (12) holds with strict inequality, the indifference map pivots counter-clockwise for increasing values of $C$. When $C = K$, there are only two maps: one for $C = 0$ holding only when the decision maker is at certainty $E$=0; and one for $C = K$ holding for all other points. In the case of a variable cost, the maps twist continuously as $C = \gamma D$ increases because of an increase in $D$.

Further, when $C = K$, condition (12) is necessary and sufficient for $\frac{dD}{\partial K} \geq 0$ at an internal optimum. This is shown by totally differentiating the first-order condition (8) with respect to $D$

and $K$, which (using the second-order condition) gives the sign of $\frac{\partial D}{\partial K}$ as the sign of $\frac{\partial^2 EU(D;C)}{\partial D \partial K}$. The latter is given by:

$$\frac{\partial^2 EU(D;C)}{\partial D \partial K} = t[p(f-1)U_{IC}(I_C;K) - (1-p)U_{IC}(I_N;K)] \quad (13)$$

Using again the first-order condition (8) shows that condition (12) implies that equation (13) is non-negative whereas when condition (12) is positive equation (13) is negative. We also remark that, when $U_{IC} = 0$, as for example in the early model with a fixed cost by Benjamini and Maital (1985), a change in the fixed cost does not affect the internal solution (even though it affects whether the taxpayer stays at the corner or jumps at the internal).

Finally, when $C = \gamma E$, condition (12) is sufficient (even if not necessary) for $\frac{dD}{\partial \gamma}$ ≥0 at an internal optimum. This follows from totally differentiating the first-order condition (5) with respect to $D$ and $\gamma$, which (using the second-order condition) gives the sign of $\frac{\partial D}{\partial \gamma}$ as the sign of $\frac{\partial^2 EU(D;C)}{\partial D \partial \gamma}$. The latter is given by:

$$\frac{\partial^2 EU(D;C)}{\partial D \partial \gamma} = [-pU_C(I_C;C) - (1-p)U_C(I_N;C)] - \gamma(I-D)[pU_{CC}(I_C;C) + (1-p)U_{CC}(I_N;C)]$$
$$+(I-D)t[p(f-1)U_{IC}(I_C;C) - (1-p)U_{IC}(I_N;C)] \quad (14)$$

Given $U_C < 0$ and $U_{CC} < 0$, the first and second square brackets are positive. As for the case of a fixed cost, condition (12) implies that the third bracket of equation (14) is positive so that the overall effect is $\frac{\partial D}{\partial \gamma} > 0$. Gordon (1989) obtains the same result when $U_{CC} = 0$ and $U_{IC} = 0$ everywhere.

## APPENDIX B: EXPERIMENT INSTRUCTIONS

Instructions ("Full Confidentiality")

This is an experiment about economic decision making. The study will last no more than 2 hours. You will receive $10 for your participation and will have the opportunity to increase this amount based on the decisions you make. Your earnings will be paid to you in cash at the end of the study. How your decisions affect your earnings is explained below.

The decisions made in this experiment are tax reporting decisions. In each round, you will be given a gross income of Lab $ 250. In each round, the probability of audit will be announced and the penalty rate on income you choose not to report will be announced. You will have to report your gross income to a tax authority and pay taxes on reported income. The tax rate is 30%. Thus, your taxes will be 0.30* (reported income). After you submit your taxes, there is a chance that you will be audited by the tax authority. The probability of audit is 30% or 20%, and the computer will use a random number generator to decide whether the audit will occur. If you are not audited, your final income for the round will be Lab $250 minus the taxes on the reported income. If you are audited and you have reported less than your full income, this will be detected by the audit and you will be required to pay the unpaid taxes plus a fine on the unpaid taxes. The fine is one time or two times the unpaid taxes. In other words, if you have unreported income and you are audited and the penalty is one time the unpaid taxes an amount which equals 2.0[1 for the unpaid taxes and 1 for the fine]*0.30*(actual income - reported income) will be subtracted from your after-tax-income to get your final income for the round. If you have unreported income and you are audited and the penalty is two times the unpaid taxes an amount which equals 3.0[1 for the unpaid taxes and 2 for the fine]*0.30*(actual income - reported income) will be subtracted from your after-tax-income to get your final income for the round.

***Examples***

These examples will demonstrate the type of decision you will be making and how your earnings will be determined.

**Example 1.** Suppose your income for the round is Lab $250 and that you report $250 as your gross income and the penalty rate is 2 times the unpaid tax. Then you will pay 0.30*$250.00 = $75.0 in taxes.

*If not audited*, your earnings for the round will be Lab $250 - $75.0 = $175.0

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**Example 2.** Suppose your income for the round is Lab $250.0 and that you report $150.0 as your income and the penalty rate is 2 times the unpaid tax. Then you will pay 0.30*$150 = $45.0 in taxes

*If not audited*, your earnings for the round will be $250 - $45.0 = $205.0

*If audited*, the audit will detect unreported income of $100 ($250 - $150). You will be required to pay the unpaid taxes plus a fine equal to 2 times the unpaid taxes which equals (1+2)*0.30*($100) = $90.0.
Your earnings for the round will be Lab $250 - $75.0 - $90.0 = $85.0

The experiment will have 16 rounds, but only one of these will count for payment. At the end of the experiment, a 16-sided die will be rolled to determine which round will count for payment. After the round is selected for payment, you will be paid in cash your earnings in that round. Each round is equally likely to be selected, but you will not know in advance which one will be chosen. For the payment, the Lab-$ are converted at a rate of Lab $ 10 = $ 1.

If you have any questions, please raise your hand and one of us will come to your desk to answer it.

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The decisions made in this experiment are tax reporting decisions. In each round, you will be given a gross income of Lab $ 250. In each round, the probability of audit will be announced and the penalty rate on income you choose not to report will be announced. You will have to report your gross income to a tax authority and pay taxes on reported income. The tax rate is 30%. Thus, your taxes will be 0.30* (reported income). After you submit your taxes, there is a chance that you will be audited by the tax authority. The probability of audit is 30% or 20%, and the computer will use a random number generator to decide whether the audit will occur. If you are not audited, your final income for the round will be Lab $250 minus the taxes on the reported income. If you are audited and you have reported less than your full income, this will be detected by the audit and you will be required to pay the unpaid taxes plus a fine on the unpaid taxes. The fine is one time or two times the unpaid taxes. In other words, if you have unreported income and you are audited and the penalty is one time the unpaid taxes an amount which equals 2.0[1 for the unpaid taxes and 1 for the fine]*0.30*(actual income - reported income) will be subtracted from your after-tax-income to get your final income for the round. If you have unreported income and you are audited and the penalty is two times the unpaid taxes an amount which equals 3.0[1 for the unpaid taxes and 2 for the fine]*0.30*(actual income - reported income) will be subtracted from your after-tax-income to get your final income for the round.

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In each round, after you have made your reporting decisions and the audit process has been finalized, you will see your earnings information from the current round and you will be shown photos of all of the audited subjects who did not report all of their income along with how much income each person shown reported. Every round the photos of those audited and who did not report all of their income will be shown to all subjects.

If you have any questions, please raise your hand and one of us will come to your desk to answer it.