Do Individuals Comply on Income Not Reported by Their Employer?

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Abstract
Individuals (e.g., the self-employed and those earning casual wages such as tips) with income not reported to the tax authority by a third party may be less likely to be detected evading taxes relative to the case in which their income is subject to third-party reporting. However, their compliance responses – to changes in the proportion of income that is reported to the tax authority, to changes in audit and tax rates, and so on – are largely unknown, in part because of the difficulty in obtaining information on individual choices in these situations. We use experimental methods to examine individual income tax compliance in settings where individuals differ in the portion of their income that is "matched" (or reported to the tax authority via third-party information) versus "non-matched" (or not fully reported to the tax authority). Our results indicate that individuals who have relatively more non-matched income exhibit significantly lower tax compliance rates than individuals who earn relatively less non-matched income. Our results also indicate that higher income levels, higher tax rates, and lower audit rates lead to increased tax evasion, but with responses that vary depending upon the proportion of matched versus non-matched income.

1. Introduction

In the United States, as with many other countries, the manner by which personal income is reported to the tax authority can vary significantly by type of employment. For example, employers are required to report their employees' wage or salary income to the taxing authority, something that we refer to as a "matched income" arrangement.[1] In contrast, the income of self-employed individuals and of those with casual earnings (e.g., tip income) is typically not reported by the paying party (or a "non-matched income" arrangement). The lack of such third-party income reporting implies that tax evasion by those earning non-matched income will be less likely to be detected via audits. As a result, individuals with non-matched income are likely to exhibit lower tax compliance than those individuals with matched income.[2]

There is a longstanding perception that third-party information affects compliance behavior. Much of the evidence has been derived from information on the self-employed. Andreoni, Erard, and Feinstein (1998) cite 1988 statistics from the Taxpayer Compliance Measurement Program (TCMP) indicating that average tax understatements for individuals with farm and sole-proprietor income (or income not subject to reporting requirements) are $1,058 and $827, respectively, compared with an average overall understatement of $289 across all individuals. As discussed in more detail later, empirical estimates of individual compliance decisions are also broadly consistent with the notion that evasion is determined in part by the source of income (e.g., wage income that is subject to matching versus income that is not subject to matching), with the amount of evasion generally higher for individuals who receive non-matched income not subject to source withholding (Clotfelter, 1983; Kagan, 1989; Feinstein, 1991; Alm, Bahl, and Murray, 1993; Joulfaian and Rider,

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[1] Such income is also subject to income tax withholding requirements and to the collection of payroll taxes.
[2] There is evidence that individuals adopt "portfolio" approaches to tax evasion, choosing to evade more in categories where expected penalties are lower (Martinez-Vazquez and Rider, 2005; Cummings, Martinez-Vazquez, and McKee, 2006).

1998).[3] Bruce (2000) also provides suggestive evidence that individuals enter into self-employment to exploit the greater tax evasion opportunities associated with self-employment. The behavior just described is, of course, consistent with rational response to the perceived lower likelihood that evasion will be detected (and punished) when the amount of information available to the tax authority is reduced. To date, however, the individual behavior of individuals in these matched versus non-matched income settings remains largely unexamined.[4]

The empirical evidence cited above is gleaned from analysis of field data. While we can obtain useful insights here, there are several aspects in which these data are inadequate for the analysis of compliance behavior. It is often impossible to disentangle evasion from responses to ambiguous instructions in the tax form, so that, for example, the numbers reported in Andreoni, Erard, and Feinstein (1998) may simply reflect the fact that the interpretations of legitimate deductions for self-employed persons are less precise than for those earning only matched wage or salary income. It is similarly impossible to know the taxpayers' individual estimates of audit probabilities and penalties. Since the field data often cover a single or a few years, there are often few changes in policy variables, something that makes it difficult to identify and so estimate individual responses to changes in enforcement efforts. Finally, we can observe compliance only for those taxpayers actually audited. Given that audits are imperfect, even when available (as from the TCMP) this information is subject to measurement errors.

For these reasons, field research on tax compliance has been complemented with data conducted via laboratory experiments. We follow this tradition here and report on behavior observed in a laboratory experiment designed to test whether individuals exhibit different tax compliance patterns when they receive different proportions of income that is perfectly detectable

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[3] With the current annual "tax gap" (the shortfall in personal income tax collection) estimated at $200 billion it is likely that a substantial portion of this lies in the unreported income earnings.

upon audit (e.g., matched income) versus income that cannot be detected with certainty (e.g., non-matched).

Our experiments mimic a situation arising in the naturally occurring environment for individuals who receive two types of income: income that is reported to the tax authority by a third party (e.g., their employer), such as wages and salaries, and also income from unreported sources such as tips or from self-employment activities in which the income is not reported by the employer to the tax authority.[5] Our experimental design allows us to examine the behavior of individuals with different proportions of income subject to third-party information as they respond to different tax and audit rates, gross and relative income, and other factors in their tax compliance decisions. This information is especially relevant to policy questions that surround how government should design income tax reporting and auditing systems.

Our results indicate that individuals who receive relatively more non-matched income exhibit significantly lower tax compliance rates than individuals who receive less non-matched income. Our results also indicate that higher income levels, higher tax rates, and lower audit rates lead to increased tax evasion, but with responses that vary depending upon the proportion of matched versus non-matched income.

Of course, while experimental methods provide several advantages in examining patterns of evasion, we must be aware of their well-known shortcomings. For example, data are drawn from somewhat artificial laboratory environments that use student subjects, and experiments have difficulty capturing the catastrophic losses that may occur with detection and punishment. Even so, there is much emerging evidence that properly designed experimental methods has much external

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[4] As discussed in more detail later, an important recent exception is the work of Gerxhani and Schram (2006).
[5] We note that tip income is far from incidental to those working in some sectors. The minimum wage for those in the food service sector was set at $2.15 at the time of the study. Depending on the potential for tip earnings, employers may pay more than this. But, for many workers in this sector, tip income may be a substantial portion of earnings.

validity, and so we believe that our approach is a useful alternative to other, more traditional methods of analysis. We address the issue of external validity when we discuss our experimental design.

2. Previous Literature

Several empirical studies have used naturally occurring data, typically from the U.S. Internal Revenue Service (IRS), to examine differential patterns of compliance across matched versus non-matched income sources. The difficulty of detecting income that is not subject to third-party reporting is described by Joulfaian and Rider (1998, p. 675):

> "In large part, this disparity in reporting compliance is attributed to the lower probability of detecting unreported self-employment income; or conversely stated, the higher cost of detecting unreported self-employment income due to the absence of third-party reporting of income and income tax withholding. In contrast, we observe nearly complete reporting of wage income that is subject to third-party reporting and withholding."

Indeed, the differing compliance behavior between self-employed individuals and individuals in wage and salary employment has been the subject of considerable study. In a recent review of the literature on taxation and self-employment, Scheutze and Bruce (2004) conclude that non-compliance among the self-employed is a significant concern, citing research that finds that the self-employed sector of the economy makes a very significant contribution to the total level of tax evasion in the nation. One of the studies in their review (U.S. General Accounting Office, 1990) estimates that for 1987 self-employed individuals account for 63 percent of the $48 billion in unreported income. Relatedly, Kagan (1989) reports findings from an IRS study of tax returns that estimates that only 50.3 percent of nonfarm proprietor income in 1979 was voluntarily reported to the IRS compared to 93.9 percent of wage and salary income. Kagan (1989) also discusses another IRS study that examined individuals who were treated as independent contractors (and who had no

income reported or withheld by a third party); this study found a low percentage of income reported overall, with 47 percent of the independent contractors not even reporting any of their earnings. Feinstein (1991) analyzes data from the IRS's Taxpayer Compliance Measurement Program, and concludes that Schedule C (own business) and Schedule F (farm) filers are much more likely to evade than the average taxpayer.[6][7] Evidence from developing countries also supports this notion. For example, Alm, Bahl, and Murray (1993) use audited individual tax returns from Jamaica, and find that evasion is significantly larger for individuals who have income sources not subject to matching requirements.[8]

The empirical literature has also found suggestive evidence that individuals enter into self-employment in order to take advantage of non-compliance opportunities. Recently, Bruce (2000) finds that higher tax rates, as well as the differential between the marginal tax rates on wage and salary and self-employment, both increase self-employment. He asserts that a likely explanation for this result is that individuals may enter into self-employment to exploit the opportunities to evade taxes; that is, higher effective tax rates on matched income may drive individuals into self-employment in order to take advantage of the associated evasion opportunities on non-matched income.[9] Anecdotal evidence from developing countries also supports this notion.

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[6] There are of course other reasons for non-compliance in the self-employed sector. For example, there may be a lack of income tax withholding or a misunderstanding of the tax system that stems from less access to paid professional tax planners.
[7] See also Witte and Woodbury (1985). They used IRS tax return data from the early 1970s, and find that tax compliance rates are higher in areas where relative more individuals are employed in the manufacturing sector (where individuals presumably earn relatively more wage and salary income), all else equal. They interpret this finding as evidence that relatively more income that is reported by a third-party, and is therefore more easily detectable, leads to relatively higher compliance rates.
[8] See also Madeo, Schepanski, and Uecker (1987). The authors recruited a pool of 71 CPAs, and presented them with a series of cases involving hypothetical taxpayers. Each case involved four factors, one of which was the source of income for the hypothetical taxpayer. The subjects then chose how much income that would be reported by the "typical" taxpayer. The authors found that their subjects predicted that those (hypothetical) individuals who earned significantly more self-employment income would likely evade more.
[9] See Robson and Wren (1999), who distinguish between the effects of marginal and average tax rates on self-employment, arguing that the latter are more related to evasion.

A recent study by Gerxhani and Schram (2006) uses experimental methods to better understand the choice of income source and its impact on subsequent tax evasion. In their design, subjects in Albania and The Netherlands are allowed to choose between earning "registered" and "unregistered" income; the amount of registered income is known with certainty to the experimenter, while the amount of unregistered income is known to the experimenter only with some probability. After income is determined, subjects must choose how much income to report and so how much taxes to pay. Registered income is audited with certainty, which implies that any income not reported will be discovered and fines imposed; unregistered income is audited with some known probability, so that subjects with unregistered income may be able to evade taxes on unreported income if they are not audited. Their results provide evidence that, when tax evasion is possible via the choice of unregistered income, subjects are more likely to choose unregistered income.

The results of Gerxhani and Schram (2006) are important and relevant to our work, since their "unregistered income" resembles what we define here as "non-matched income". Their focus, however, is on whether individuals are more likely to choose an income source (or an "occupation") with greater amounts of "unregistered income" – indeed, individuals are more likely to make this choice – and whether subsequent evasion behavior differs across taxpayers who choose unregistered income versus those who choose registered income occupations – indeed, again, behavior differs. Put differently, Gerxhani and Schram (2006) are mainly interested in examining the performance of the "informal sector" (or the sector in which individuals are not as likely to be caught if they do not report fully their income): are individuals more likely to choose to work in the informal sector because they may then be better able to cheat on their taxes? By their choice of countries in which

to conduct the experiments, Gerxhani and Schram (2006) also investigate the effect of trust in the fiscal institutions on the individual choice of whether to work in the formal or the informal sector.

In contrast, our interest here is in the design of actual institutions of tax collection. Specifically, we investigate two questions: how is individual tax reporting affected when the use of third-party sources of information varies across income types, and how do individuals with different proportions of income subject to third-party information respond to changes in tax rates, audit rates, gross income, and other factors in their tax compliance decisions? We are mainly interested in examining the performance of the tax authority, especially in the design of fiscal institutions that are more effective in collecting taxes.[10] While the Gerxhani and Schram (2006) study yields useful insights, clear conclusions regarding the determinants and magnitude of tax evasion among taxpayers subject to different reporting requirements remain elusive. Our experiments are the first to provide insights on these issues.

Why do we use experimental methods? As noted earlier, the primary difficulty here is the lack of fully reliable naturally occurring data, given that evasion is so difficult to capture.[11] In addition, there are other confounding effects with naturally occurring data that make clear estimates of tax non-compliance difficult to obtain, such as the existence of ambiguous tax laws and the

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[10] Our experimental design differs in many significant respects from that of Gerxhani and Schram (2006). Among other things, we impose the proportion of income that is matched versus non-matched rather than allowing subjects to choose this proportion. We wanted to isolate the compliance decision from the choice of employment. Our setting reflects a common naturally occurring setting such as service personnel in restaurants and bars. In our design we vary the audit rates on non-matched income; we require subjects to earn income by their performance in a simple task (rather than impose a fixed schedule of random incomes from which subjects are allowed to choose); we use a different set and range of fiscal parameters (e.g., tax, audit, and penalty rates); we use different group sizes; we use different subject pools; we use a larger number of rounds (e.g., 30 versus 8). We do not include a public good financed from subject tax payments although we are cognizant of the fiscal exchange argument but suspect that it is manifest through the political market rather than a perceived link between own tax compliance and the *quantity* of the public good supplied. Alm, Jackson, and McKee (1993) demonstrate such a public choice link in a set of lab experiments.

[11] For example, Clotfelter (1983) states, in reference to data from the TCMP that "…income from moonlighting and cash-only businesses is very difficult even for trained auditors to identify."

presence of non-filers.[12] Even if naturally occurring data on the individuals with different amounts

of income subject to third-party information are available, such data are subject to the obvious

problem that there are numerous factors that may affect behavior, factors that are difficult (if not

impossible) to identify and to control for; put differently, naturally occurring data are unable to

differentiate between the various causes that may encourage (or discourage) evasion, and such data

are especially unable to control for these different causes. Experimental data offer significant

advantages: compliance rates from experiments are accurate, and each variable that affects

compliance can be identified and controlled for in the experimental design. In particular, our

experimental design specifically allows us to isolate the lower detectability that may accompany,

say, self-employment income versus wage income, in order to determine the impact on the

compliance behavior of subjects. Our design also allows us to vary the relevant fiscal parameters,

in order to determine the impact of changes in, say, audit rates on compliance decisions. The next

section discusses our experimental design.

3. Experimental Design

Our experimental structure attempts to replicate the fundamental elements of the voluntary

reporting system of the U.S. individual income tax.[13] Subjects earn income by performing a simple

task, and they are told what percentage of their total income is "matched income" and what

percentage is "non-matched income". They then report none, some, or all of each type of income to

the taxing authority, and pay taxes at an announced rate on all income that is reported. Income not

reported is not subject to the income tax. However, individuals may be audited, where the audit is

randomly determined with a known and announced probability. If a subject is audited, any matched

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[12] See Erard and Ho (2001) for an empirical analysis of non-filers.

income that is not reported is discovered; any non-matched income that is not reported is discovered but only with some probability, also known and announced. If the individual is not in compliance and if this noncompliance is detected, then he or she pays the additional taxes owed plus a penalty that is a multiple of the unpaid taxes.

This setting provides for the necessary degree of "parallelism" to the naturally occurring world that is crucial to the applicability of experimental results (Smith, 1982; Plott, 1987). The experimental setting need not attempt to capture all of the variation in the naturally occurring environment, but it should sufficiently recreate the fundamental elements of the naturally occurring world if the results are to be relevant in policy debates. In this regard, our experimental design uses tax language, which is presented via the subject interface, requires that the subjects earn income in each period, and disclose this income in the same manner as in the typical tax form. As in the naturally occurring setting, there is a time limit on the filing of income, and the clock at the bottom of the screen reminds the subjects of this. There is also a penalty for failing to file on time.

The experiment proceeds in the following fashion. Each subject sits at a computer located in a cubicle, and is not allowed to communicate with other subjects. The instructions are conveyed by a series of computer screens that the subjects read at their own pace. Clarification questions are addressed after the subjects have completed the instructions and two practice rounds. The subjects are informed that all decisions will be private; the experimenter is unable to observe the decisions and does not move about the room once the session starts. This reduces, as much as possible, both peer and experimenter effects that could affect the decisions of the subjects. All actions that subjects take are made on the computer. In each round of the experiment, subjects earn income based upon their performance in a simple computerized task, in which they are required to move

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[13] Our basic experimental design and platform is similar to that of Alm and McKee (2006). The major difference here, of course, is the incorporation of matched versus non-matched income.

numbers in the correct order from one location on the computer screen to another location.[14] The

subject who finishes the task with the quickest time earns the highest income (100 "lab dollars");

the second and third place finishers earn 90 lab dollars each, the fourth and fifth place finishers earn

80 lab dollars each, and so on, with ties broken randomly. Subjects are informed of their earnings

and those of the others in their group to ensure that they believe the relative nature of the earnings.

These earnings represent the only information subjects have of other participants.

   After earning income, subjects see a screen that reports their income as well as the tax policy

parameters.[15] These parameters include the audit rate, the penalty rate, and the tax rate.

Importantly, subjects are told the percentage of their total income that is matchable (and the

corresponding percentage that is non-matchable). They are also told that any matchable income that

is unreported will be discovered with certainty in the event of an audit, while any non-matchable

income that is unreported will be discovered in an audit, but only with some known and announced

probability.[16] Subjects then choose how much of their matched and non-matched income to report

to the tax authority. They are able to report any amount between zero and their total earnings (no

decimals) of each type of income. The computer automatically reports taxes owed, and it also

computes tax liability based on the fractions of matched and non-matched income reported.

Subjects are able to experiment with different income reports during the time allowed for filing.

For each potential report, the computer computes their final income in the event the subject is

audited and in the event the subject is not audited.[17] Subjects may also view their history of

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[14] See Appendix 1 for an image of the income earnings task.

[15] See Appendix 2 for an image of the page used to report income.

[16] During the instructions, subjects are given the definitions of matched and non-matched, and are told that a real world example of non-matched income is tip income. As noted above, tip income can constitute a significant share of total income for typical workers in the food and beverage service sector. During debriefing, our subjects indicated that they knew that tips could make up a considerable portion of earnings in the field.

[17] This calculator simply computes the net income the subject would receive in the two alternate states of the world: audited and not audited. We include this feature so that we can focus on the behavioral decision making aspect of the setting rather than be concerned with differences in subjects' ability to compute state-contingent outcomes.

previous rounds during this period. The timer counts down the remaining time and begins to flash

when there is fifteen seconds remaining.

Audits are determined by the use of a "virtual" bingo cage that appears on each subject's

computer screen. A box with 10 balls (blue and white) appears on the screen following the tax

filing. The balls begin to bounce around in the box and after a brief interval a door opens at the top

of the box. If a blue ball exits, the subject is audited; a white ball signifies no audit. The fraction of

blue balls determines the audit probability. The audit applies only to the current period

declarations, not to previous (or future) periods. The computer automatically deducts taxes paid

and penalties (if any are owed) from subjects' accounts. Any taxes and penalties paid are not

distributed to the subjects. As noted above, the tax revenues are not used to provide a public good

in this set of experiments to ensure that the subjects focus on the individual income disclosure

decision.

After-tax income for each round is represented by the equation:

$$\textit{After-tax Income} = G - t\,G\,[M * r_m + u * r_u] - A\,t\,(1+F)\,G\,[M\,(1-r_m) + D\,u\,(1-r_u)],$$

where

G	= gross (earned) income
T	= tax rate
M	= proportion of gross income that is matched
r_m	= proportion of matched income reported by the subject
u	= proportion of gross income that is non-matched = $(1\text{-}M)$
r_u	= proportion of non-matched income reported by the subject
A	= 1 if individual is audited and 0 otherwise
F	= penalty rate on unreported taxes
D	= if subject is detected on not fully reporting non-matched income and 0 otherwise

Subjects are informed that they keep their after-tax earnings at the end of the experiment, converted

from lab dollars to U.S. dollars at the rate of 100 lab dollars to 1 U.S. dollar, and paid in cash and in

private. After income is reported and an audit (if any) is determined, subjects see one final screen

that summarizes everything that happened during the round. This process is repeated for a fixed (but unannounced) number of rounds.

The experimental design applies five combinations of matched versus non-matched income: 0 percent, 25 percent, 50 percent, 75 percent, and 100 percent non-matched (and the corresponding matched percentages). There are three different tax rates: 20 percent, 35 percent, and 50 percent. We use a between group design for both of these variables; that is, these parameters are varied only between sessions, and any particular subject sees only one combination of matched and non-matched income and only one tax rate.

The probability of audit is a treatment variable, and is assigned a value of 10 percent or 30 percent. These rates are much higher than actual *full* audit rates in the United States. However, the IRS conducts a range of audits and for many types of audits the rates are quite high.[18] In our design the probability that an individual is detected evading taxes varies between matched and non-matched income. The probability of detection is 100 percent for matched income; if an individual is audited, any matched income that is unreported is discovered with certainty. However, for non-matched income the detection rates vary among 25 percent, 50 percent, and 75 percent. The penalty rate on unreported income is set at a rate of 50 percent; on detected non-compliance an individual must pay discovered undeclared taxes plus a penalty of 50 percent of undeclared taxes.

Each session involves two stages, each with 15 rounds, with the audit rate the only parameter that changes between the two stages. Earnings per subject were between $19 and $37 range, based upon performance in the income earning component, tax reporting, and chance (i.e.,

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[18] While overall audit rates are quite low, among certain income and occupation classes they are more frequent. The oft-reported IRS audit rate (currently between one and two percent) is somewhat of an understatement. This reported rate usually refers to full audits and the IRS, in fact, conducts a wide range of audits including line matching and requests for information. These are much more frequent. For example, in 2005 only 1.2 million individual returns (or less than one percent of the 131 million individual returns filed) were actually audited. However, in that year the IRS sent 3.1 million "math error notices" and received nearly 1.5 billion "information returns" from third parties, which are used to verify items reported on individual income tax returns.

the audit process). The experimental design requires the administration of nine sessions, as outlined in Table 1. Sessions consist of 16, 14, or 12 subjects, depending upon on show up rates.[19] In all, 124 subjects participated in the experiment, resulting in 3,720 (or 124 * 30) observations.

The experimental platform consists of 16 notebook computers, a server machine, and software designed for this series of experimentation. Sessions were conducted on the University of XXXX campus using students recruited via announcements on campus. Potential subjects signed up via a web page and are invited to participate in a specific session by e-mail. Subjects were not permitted to participate in more than one session, only subjects recruited specifically for a session were allowed to participate, and no subject had prior experience in this experimental setting. Methods adhere to all guidelines concerning the ethical treatment of human subjects.

4. Behavioral Hypotheses and Analytical Approach

The experimental setting described above allows for an examination of several behavioral hypotheses. The first hypothesis is our main focus:

H1: *Individuals are more likely to evade taxes when a larger share of their income is of the type that is not perfectly detectable by the tax authority; that is, the compliance rate falls as the percentage of income received as non-matched income increases.*

The ability of the tax authority to detect the true level of income clearly affects the expected value of compliance versus evasion, and, accordingly, affects compliance in a rational tax evasion model. However, this issue remains an empirical question, for several reasons. First, as has been demonstrated in numerous settings, individuals may not act in accordance with a rational tax evasion model. Second, and more importantly, we are able to examine the impact in our controlled experimental environment of changes in the exact probability at which certain income types are

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[19] Subjects are divided into two equal sized groups. This provides the subjects further anonymity since the subjects do not know the identities of those in their group.

detected. This is a crucial advantage of experimental methods over data (even if available) from the naturally occurring world. If we are able to show that less than perfectly detectable income increases tax evasion, an examination of individual responses to the probability of detection provides information that can be used in evaluating policies that affect the likelihood that certain income types could be detected upon audit.

The remaining hypotheses have been examined before in the literature. We conduct a reexamination here mainly for the purposes of complementing the matched/non-matched income component of the study but also since our overall experimental design can be validated if our results here match those of earlier studies.

A second hypothesis is that evasion increases with higher tax rates:

H2: *Higher tax rates have an uncertain impact on compliance.*

It is well established that, in theory, a higher tax rate has conflicting effects on compliance (Allingham and Sandmo, 1972). A higher tax rate increases the incentive for cheating, thereby increasing the amount of evasion. However, a higher tax rate also lowers income, and, with decreasing absolute risk aversion, lower income makes an individual more risk averse; reducing tax evasion. However, as Yitzhaki (1974) demonstrates, when the penalty is imposed on evaded taxes (not evaded income), the substitution effect disappears. In this circumstance, theory predicts that tax compliance should actually increase as the tax rate increases. However, most empirical and experimental work finds that there is a positive relationship between tax rates and tax evasion.

Similarly, audit rates change the expected value of reporting income versus not reporting, and should affect tax compliance. It is straightforward to demonstrate via comparative statics exercises of the evasion gamble that compliance increases with higher audit rates:

H3: *Higher audit rates lead to higher levels of tax compliance.*

Wealth may also affect tax compliance by affecting the marginal utility of another dollar of income and, correspondingly, one's risk preferences, although this effect depends upon one's attitudes toward risk:

H4: *Increases in income or wealth have an uncertain impact on tax compliance.*

An important consideration in individual choices is the expected value of reporting income versus not reporting. Table 2 reports the difference in the expected value of reporting 100 dollars of income versus not reporting any income for matched and non-matched income, for each tax rate, audit rate, and non-matched income detection probability combination used in experimental design. If individuals followed simple mathematical models perfectly and were risk neutral, these expected value calculations would predict behavior without error, and individuals would exhibit all-or-none behavior, choosing to report, say, all matched income or none it (or, say, all non-matched income or none of it).[20] However, individuals may not always be risk neutral. They also may not follow a simple model of expected income maximization. Further, individuals may have other reasons to comply or not, such as moral values associated with complying or cheating. Finally, subjects may focus on certain parameters more than others simply due to their priors, as derived from the media or other sources. For example, an individual may over- or underweight the tax rate simply because he or she is familiar with it from prior experience.

Aside from these reasons, the expected value is still important because a rational tax evasion model likely explains a significant portion of individual behavior. We have structured the parameters such that, for a risk neutral individual, it is rational to evade in most cases, in order to increase the parallelism of our design with that of the naturally occurring world where evasion is

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[20] For example, consider the impact on after-tax income of a change in the proportion of matched income r_m that is reported by the individual. This impact is positive if $A (1+f) > 1$, and is negative otherwise. Similarly, the impact on after-tax income of a change in the proportion of non-matched income r_u that is reported by the individual is positive if $A D 1t+f) > 1$, and is negative otherwise. These conditions indicate that the reporting decision is an all-or-none

typically the rational choice. Thus, the difference between the expected value of compliance and

the expected value of non-compliance is negative in all but one case (e.g., where there is a low tax

rate and a high audit rate on matched income). Evading non-matched income always carries a

larger expected gain relative to matched income, all else equal.

We evaluate these hypotheses in several ways. Aside from analysis of simple descriptive

statistics, our primary approach consists of a generalized least squares (GLS) regression model that

explains income tax compliance as a function of the fiscal parameters plus gross income. The

model includes subject-specific effects to control for individual-specific characteristics, and also

allows for heteroskedasticity across individuals. Income tax compliance is measured as the

percentage of gross income reported to the tax authority. The baseline model is summarized as:

$$\textit{Percent of Gross Income Reported}_{i,t} = \beta_0 + \beta_1\,\textit{Gross Income}_{i,t} + \beta_2\,\textit{Percent Non-Matched}_{i,t}$$
$$+ \beta_3\,\textit{Tax Rate}_{i,t} + \beta_4\,\textit{Audit Rate}_{i,t} + \beta_5\,\textit{Probability of Detection}_{i,t} + \varepsilon_{it},$$

where i and t are individual and round indices and $\varepsilon_{it} = u_i + w_{it}$. The traditional error term is

denoted by w_{it}, and is assumed to meet all of the usual requirements. The individual-specific effect

is denoted by u_i and controls for individual level heterogeneity. We have estimated a wide variety

of alternative specifications. For example, we have changed the dependent variable to Gross

Income Reported, and we have included other explanatory variables (such as controls to denote the

round). Our results are quite robust to alternative specifications, and we report several alternative

specifications.

5. Results

The simplest analysis of our experimental results examines descriptive statistics on the

effects of the various fiscal variables (e.g., matched versus non-matched income, tax rates, audit

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decision: either individuals report all matched (or non-matched) income or they report none, depending upon the values

rates, income) on the level of compliance rates, where "compliance rate" is calculated by dividing

reported income by gross (or total) income.

The overall compliance rates for matched versus non-matched income are:

Income Type	Compliance Rate
Total	47.6 percent
Matched income	54.2 percent
Non-matched income	41.4 percent

These raw results indicate that individuals report a much lower percentage of their non-matched

income relative to matched income, providing evidence in support of the primary hypothesis (H1).

These differences are statistically significant. Presenting the data graphically allows us to

investigate some general behavioral tendencies and verify that the subjects show behavior that is

consistent with broad predictions.

Figure 1 presents the distribution of average tax compliance rates for individuals, over 30

rounds, for matched and non-matched income. The histogram presents groupings over aggregate

compliance rates. As with much of the earlier literature (e.g., Alm, Jackson, and McKee, 1992)

observations are concentrated at the extremes. Figure 1 also indicates that a noticeably larger

portion of the non-matched sample falls into the 0-20 average compliance rate range, while a larger

percentage of the matched sample falls into the 81-100 range. Indeed, 49.9 percent of the subjects

exhibit compliance rates that fall into the 81-100 percent range on their matched income, while only

32.8 percent of individuals exhibited compliance rates this high for their non-matched income.

Figure 2 presents overall compliance rates by the percentage of income that is non-matched,

or H1 (e.g., compliance decreases as more of an individual's income is non-matched). These

aggregate data do not support our conjecture that compliance will fall as the share of non-matched

income increases. There is a slight downward trend overall but compliance is actually highest when

of the fiscal parameters.

subjects receive half of their income from non-matched sources. Of course, these simple

presentations do not control for other factors that may influence tax compliance behavior.

Figure 3 presents average tax compliance rates by the tax rate. As noted in H2, it is

theoretically unclear how compliance should respond to the tax rate. Our results here indicate that

tax compliance decreases with higher tax rates, consistent with other empirical (Clotfelter, 1983;

Alm, Bahl, and Murray, 1995) and experimental (Alm, Jackson, and McKee, 1992) work. The drop

is much larger moving between the 20 and 35 percent tax rates than between the 35 and 50 percent

rate. Figure 4 shows compliance rates by audit rates (H3). As expected, compliance rates increase

as the audit rates increases. Figure 5 presents compliance rates by income. While compliance

increases between 60 and 70 lab dollars of income, average compliance rates decline fairly steadily

as income rises above 70 lab dollars.

Our data set constitutes a panel of 124 subjects making 30 individual decisions. We elected

to utilize a feasible generalized least squares panel estimation procedure correcting for panel

(individual) specific heteroskedastic errors. Results from several GLS regression models are

presented in Table 3. Since our interest is in the overall level of compliance, we do not estimate the

compliance levels for matched and non-matched income separately. The dependent variable is the

percent of total income reported to the tax authority.

Coefficient estimates isolate the individual effects of each fiscal variable on compliance

from every other factor variable in the specification, including subject-specific effects. Controlling

for subject-specific effects is especially important because this allows us to isolate external factors

that could blur the results, such as animosity toward the tax system, fairness, moral obligations to

pay taxes, and the like, and also allows for a precise examination of the effect of changes in the

included variables.

Results from the baseline model (Model 1) are presented in the first column of Table 3. These estimation results support the primary hypothesis (H1): tax compliance decreases as individuals earn larger shares of non-matched income. Our estimates indicate that the tax compliance rate declines by 1.6 percentage points as the "Percent Non-matched" increases by 25 percentage points. Relative to an average tax compliance rate of 47.6 percent, this indicates a fairly small elasticity. The probability that an individual's non-matched income is detected upon audit is also varied.[21] As expected, our estimation results indicate that a higher "Audit Success Rate" (or the probability that unreported non-matched income is discovered, in the event of an audit) leads to higher rates of tax compliance. More specifically, the tax compliance rate increases by 3.8 percentage points following an increase in the audit success rate of 25 percentage points.

Several of the other variables included in this regression are deserving of attention. The "Tax Rate" is a statistically significant determinant of compliance (H2). A tax rate increase from 35 percent to 50 percent lowers compliance by 11.6 percentage points, a large change when considering average compliance rates. Higher audit rates ("Audit Probability") lead to significantly higher rates of compliance (H3). Increasing the audit probability from 10 to 30 percent increases compliance by 4.9 percentage points, all else equal. These tax rate and audit rate results are consistent with the earlier findings of Alm, Jackson, and McKee (1992). Our results also indicate that higher income is associated with significantly lower levels of tax compliance. More specifically, an increase from 90 to 100 lab dollars lowers the percentage of income reported by 6.6 percentage points. "Gross Income" has a negative and significant impact on the average compliance rate.

Model 2 (Table 3) adds a dummy variable denoting whether the individual denoting whether an individual prepares his or her own tax return ("Prepare Taxes"). Individuals checking "no" on

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[21] Recall that the probability of detection upon audit for matched income is fixed at 100 percent.

this follow up question are likely to be included as dependents on their parents' tax returns. Thus, this variable may capture whether the individual is independent, has additional work experience, and, perhaps most importantly for our purposes, has thought about the audit possibilities in the naturally occurring setting in which tax decisions are made. Interestingly, the coefficient on this variable is significant and negative, so that individuals with greater experience with the tax system are less likely to comply in our setting. This was the only variable from the set of demographic characteristics collected at the completion of the experiment that was significantly correlated with the dependent variable. Our results indicate that income reporting rates are 20.7 percentage points lower for individuals who file their own tax return than for those who do not.[22] Other results from this model are largely unchanged; in particular, the coefficient on the percent of income that is not matched is still negative and significant.

Model 3 adds to Model 1 the subjects' total earnings up to the previous round in the experiment. We denote these cumulative earnings as "wealth". Individuals may attempt to enhance their earnings if they have performed poorly in previous rounds, resulting in a negative relationship between wealth and non-compliance. Alternatively, wealthier individuals could have different risk preferences or they may be better able to afford gambling. Results indicate that higher wealth is associated with less tax compliance behavior (H4). However, with this specification, the coefficient on non-matched income is no longer significant. Since compliance is lower when the fraction of non-matched income is higher, and the audit productivity on this type of income is low, wealth is correlated with the fraction of non-matched income. The degree of multi-collinearity is sufficiently high that we cannot draw strong inferences from Model 3.

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[22] Another potential explanation could be that "Prepare Taxes" is simply picking up age; that is, perhaps older people are more likely to prepare their own taxes, and they may have differing tax compliance patterns. However, a model with age included (not reported) did not identify any statistical relationship between age and tax compliance behavior.

Model 4 includes a variable to denote whether an individual was audited in the previous round ("Audit Last Round"). Since our audit process is purely random, a rational subject will treat each round as independent, so that the predicted coefficient on lagged audit is zero. As the results in Table 3 show, this is the case here. The coefficient on non-matched income is (weakly) significant.

In sum, our results suggest that higher levels of non-matched income are associated with lower levels of tax compliance. The effect is reasonably robust across specifications.

6. Conclusions

Our experimental results indicate that individuals who earn a larger share of income that is difficult to detect exhibit significantly lower rates of tax compliance. In addition, our results show that compliance increases when income that is not perfectly detectable carries higher rates of detection. Other observed results confirm the findings of earlier studies. Lower tax rates and higher audit rates lead to significantly higher tax compliance rates. Furthermore, individuals who prepare their own tax returns and wealthier individuals tend to evade significantly more.

Even so, the question is still not completely resolved as to why the self-employed (whose income is presumably more difficult to detect) exhibit differing *rates* of compliance, and also different *responses* in their compliance decisions, than those who are in wage and salary employment. Our research provides some evidence that one possible explanation for higher rates of non-compliance among this group is lower rates of detection associated with their income. However, it is obvious that other factors may also affect compliance among the self-employed, such as the lack of income withholding for this group or the existence of more complicated tax returns

than those of individuals who earn wage and salary income. More research is required to verify the effects of these other factors.

Some policy conclusions follow from our results. A tax authority adopting an endogenous selection audit rule, will likely wish to increase its audit effort on taxpayers who earn income that cannot be matched with reports from the payer. Since U.S. filers provide an occupation class, the IRS could select returns for audit among occupations that generally have higher proportions of not-matched income. It may also be possible to subject matched income to higher withholding rates for those occupation classes.

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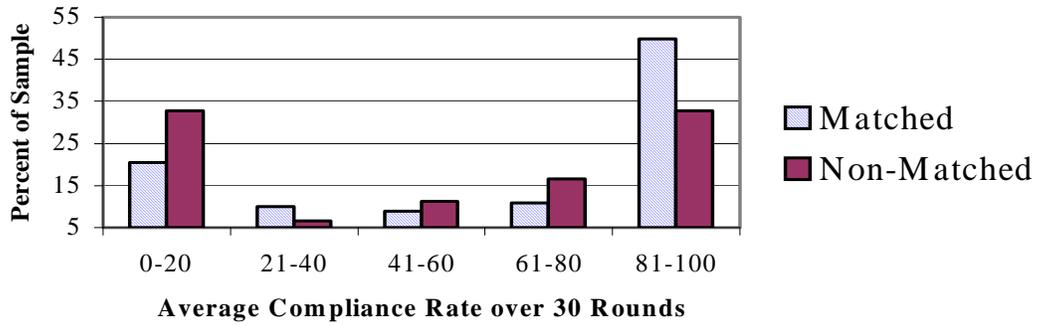
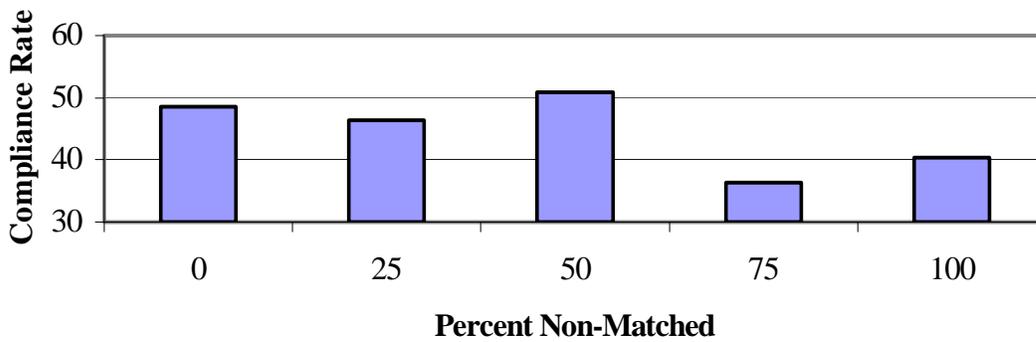**Figure 1: Distribution of Average Compliance Rates**

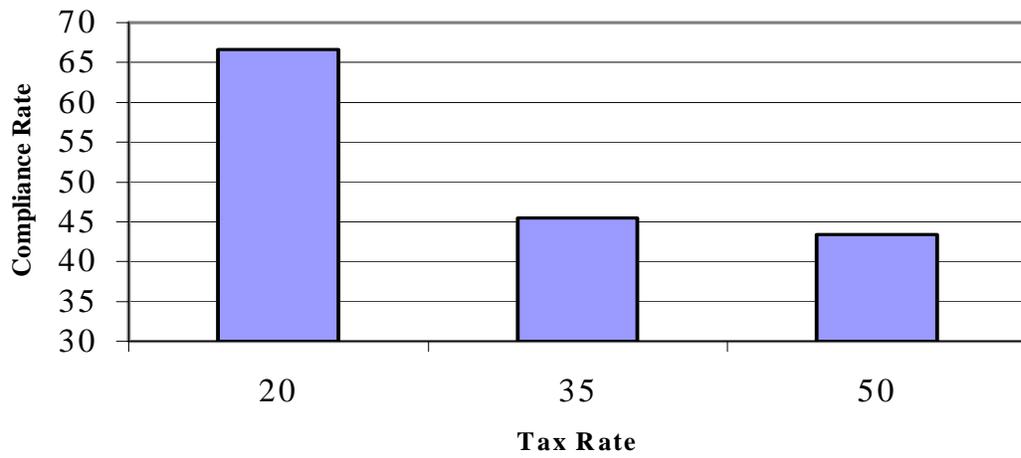**Figure 2: Compliance Rates by Non-Matched Share**

Figure 3: Compliance Rate by Tax Rate
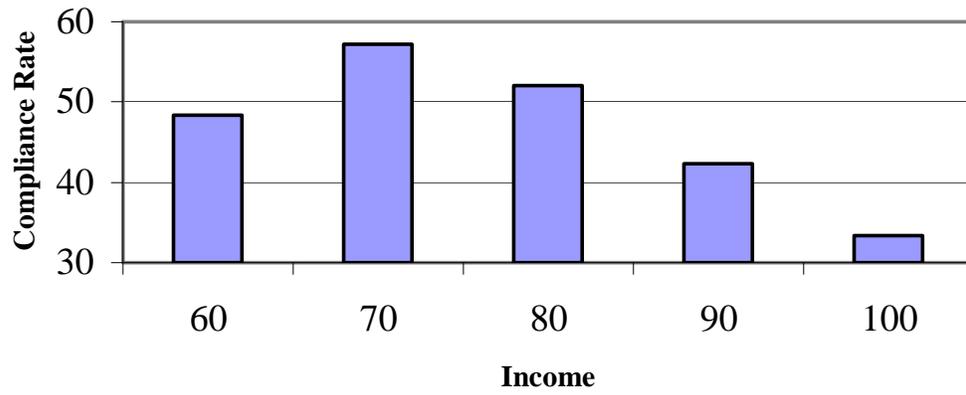

Figure 4: Compliance Rate by Audit Rate

Figure 5: Compliance Rate by Income

Table 1: Experimental Design

Treatment	Percent Non-Matched	Tax Rate	Audit Probability	Probability of Detection
1	0	35	10 and 30	-
2	25	35	10 and 30	50
3	50	35	10 and 30	50
4	75	35	10 and 30	50
5	50	35	10 and 30	75
6	50	35	10 and 30	25
7	50	20	10 and 30	50
8	50	50	10 and 30	50
9	100	35	10 and 30	50

Table 2: Should a Risk Neutral Individual Comply?

Matched Income

Tax Rate	Audit Rate	Expected Value of Compliance - Expected Value of Non-Compliance
35	10	-26.5
20	10	-13.0
50	10	-40.0
35	30	-9.5
20	30	1.0
50	30	-20.0

Non-Matched Income

Tax Rate	Probability of Detection	Audit Rate	Expected Value of Compliance - Expected Value of Non-Compliance
35	50	10	-28.2
35	75	10	-29.8
35	25	10	-26.6
20	50	10	-14.0
50	50	10	-42.5
35	50	30	-14.7
35	75	30	-19.5
35	25	30	-9.8
20	50	30	-1.9
50	50	30	-27.4

These figures are based upon an income of 100 lab dollars and a penalty rate of 50 percent of unreported income.

Table 3: Generalized Least Squares Regression Results

Variable	Dependent Variable: Percent of Total Income Reported			
	Model 1	Model 2	Model 3	Model 4
Percent Non-Matched	-0.062**	-0.054**	0.021	-0.053*
	(0.027)	(0.026)	(0.026)	(0.027)
Audit Success Rate	0.150***	0.104*	0.106*	0.163***
	(0.057)	(0.056)	(0.055)	(0.058)
Gross Income	-0.660***	-0.693***	-0.482***	-0.677***
	(0.065)	(0.064)	(0.064)	(0.067)
Tax Rate	-0.776***	-1.023***	-0.882***	-0.782***
	(0.098)	(0.098)	(0.095)	(0.100)
Audit Probability	0.245***	0.245***	2.087***	0.289***
	(0.070)	(0.068)	(0.126)	(0.074)
Prepare Taxes	-	-20.744***	-	-
	-	(1.524)	-	-
Wealth	-	-	-0.034***	-
	-	-	(0.002)	-
Audit Last Round	-	-	-	-1.645
	-	-	-	(1.865)
Constant	119.88***	139.43***	108.93***	119.48***
	(7.35)	(7.31)	(7.09)	(7.49)
Wald Statistic	200.1***	395.4***	517.2***	201.2***
Log Likelihood	-19244	-19154	-19099	-18549

Entries are generalized least squares panel regression coefficients with standard errors in parentheses.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

All percentages are on a 0-100 scale.

There are 3,720 observations for models 1, 2, and 3, utilizing 124 subjects.

Model 4 utilizes 3,580 observations, also with 124 subjects. Here the first round was dropped for the lagged audit variable.

Appendix 1: Earnings Tax Image

Subject 1   Earn Your Income   Training Round!

Completed Product

? ? ?
? ? ?
? ? ?

Sort These

2 8 1
6 7 5
3 4 9

Timer
0.0

Continue

There are two blocks above. The right has nine numbers in a random order (selected by the computer). To earn income you must move these numbers to the block on the left and put them in ascending order (lowest number in the upper left corner, next lowest to the right, and so on). Use the mouse to click the number you want to move first. The computer will move this number to the left block. Then click on the number you want to move next and so on. You must move the numbers in the correct order (smallest to largest). When you click the first correct number the timer will begin and continue until you have finished moving all the numbers. Your earnings depend on how quickly you complete this task. The first person to finish will get the highest income, the second person, the second highest income and so on. You will learn your earnings on the next page.

Previous Page   Next Page

Appendix 2: Tax Form Image

Note: this screen is presented for illustration purposes. The experiments reported here did not allow for the reporting of deductions and so that portion of the above screen does not appear in the sessions analyzed here.