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Multiple Modes of Tax Evasion:

Theory and Evidence from the TCMP

March 6, 2003

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ABSTRACT

In general, theoretical and empirical studies of tax compliance conclude that increasing penalties and detection probabilities increase compliance. However, these conclusions are based on relatively simple models with a single mode of tax evasion. In this paper, we examine the theoretical and empirical implications of accounting for multiple modes of tax evasion. We find that an increase in enforcement effort in one mode has an ambiguous effect on compliance in the targeted mode as well as the other mode. In order to gain greater insight into taxpayer behavior, we use the 1985 TCMP to estimate an empirical model with two modes of evasion: income reporting and deductions reporting compliance. We find that taxpayers use alternative modes of evasion as substitutes. In other words, an increase in enforcement effort in a given mode leads to an increase in compliance in the targeted mode and a decrease in compliance in the other mode. We use our empirical estimates of the parameters in the model to conduct several simulations. We find that the net revenue effect of increased enforcement effort is positive.

The Internal Revenue Service (1988) estimates that 99.5 percent of wage and salary income is voluntarily reported for federal personal income tax purposes, while 90.7 percent of realized long-term capital gains are voluntarily reported. Such patterns of voluntary reporting compliance among sources of income may be explained by their differential tax and enforcement treatment. For example, the higher statutory tax on wage and salary income means that the benefit in terms of unpaid tax from underreporting wage and salary income in a given amount is greater than from underreporting capital gains, but the risks of getting caught underreporting wage and salary income are considerably higher because they are subject to third party reporting and withholding of tax and capital gains generally are not.[1] In short, the differential tax and enforcement treatment of particular line items, like wage and salary income and capital gains in the example above, create opportunities for taxpayers to manage the risk-to-benefit ratio to tax evasion by misreporting a variety of line items. We refer to such strategies as multiple modes of tax evasion.

Many theoretical and empirical studies examine the determinants of tax compliance, but these models typically assume a single mode of tax evasion.[2] It is

[1] Also, non-compliance arising from negligence carries lighter penalties than non-compliance due to fraudulent behavior. U.S. taxpayers who understate their tax liabilities may be subject to civil or criminal penalties. Civil penalties are generally applied at a rate of 20 percent of the portion of the underpayment of tax resulting from a specified misconduct. In cases of fraud, which involve clear and convincing evidence that the taxpayer engaged in intentional wrongdoing, a criminal penalty may be applied. A willful attempt to evade tax is a felony.

[2] For studies examining a single mode of evasion see, for example, Allingham and Sandmo (1972), Yitzhaki (1974), and Clotfelter (1983). Several studies consider multiple modes of tax evasion including Pencavel (1979), Cowell (1981), Sandmo (1981), Klepper and Nagin (1989), Feinstein (1991), Cremer and Gahvari (1994), and Cowell and Gordon (1994). Their contributions are discussed in greater detail below.

important to gain greater insight into the effect of enforcement strategies on the optimal compliance behavior of taxpayers in more realistic settings with multiple modes of tax evasion. For example, increasing the probability of detection in one mode may simply lead to decreased compliance in other modes. In fact, the resulting revenue increase from he mode targeted for increased enforcement effort may be more than offset by deteriorating compliance in others.[3]

We explore these issues by developing a model with two modes of tax evasion. Assuming risk-averse taxpayers and fixed and independent detection probabilities and penalties, we find that an increase in a detection probability in one mode has an ambiguous effect on compliance in both modes. In order to resolve this fundamental ambiguity we estimate simultaneous equations of income and deductions reporting compliance, using data from the Internal Revenue Service's (IRS) 1985 Taxpayer's Compliance Measurement Program (TCMP). Our empirical findings support the widely held belief that compliance varies positively with detection probabilities in the targeted mode. We also find that increased enforcement effort in the targeted mode leads to decreased compliance in the other mode. Finally, we use our estimates to simulate alternative enforcement strategies. Our simulations show that the revenue increase due to increased enforcement effort in the targeted mode is only partially offset by deteriorating compliance in the other mode. In other words, the net-revenue effect of increased enforcement effort is positive.

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[3] Cummings et al. (2001) provide experimental evidence on compliance behavior with multiple modes of tax evasion. They find that increased enforcement effort in one mode of evasion can lead to lower overall tax compliance.

We proceed as follows. In the next section, we briefly review the literature on tax compliance. Then, we present a model with two modes of evasion. In Section Four, we describe our empirical approach including the data and variable construction. We discuss our empirical results in Section Five. Section Six summarizes our findings and offers suggestions for future research.

A Brief Review of the Literature

Given the vast literature on tax compliance, we cannot do justice here to the entire body of literature.[4] Therefore, we limit our review to studies, like the present one, that examine multiple modes of tax evasion and/or use TCMP data. In their seminal papers, Allingham and Sandmo (1972) and Yitzhaki (1974) assume a single mode of evasion (i.e., income reporting) with an associated detection probability and penalty. They find that these two tax enforcement parameters have a positive effect on compliance. In other words, an increase in enforcement effort leads to an increase in compliance. Pencavel (1979), Cowell (1981), and Sandmo (1981) add labor supply to the model and, thereby, make income endogenous. In the case of endogenous income, the effect of the enforcement parameters is ambiguous.

Although several papers, including Pencavel (1979), Christiansen (1980), and Cowell (1985), distinguish between different forms of tax evasion, these studies do not explicitly recognize that taxpayers may employ them to manage the risk of detection. An important exception is Klepper and Nagin (1989) who examine line item reporting

[4] Andreoni, Erard, and Feinstein (1998) and Alm (1999) provide excellent reviews of the tax compliance literature.

compliance. They argue that there is a substitution process for reporting compliance among line items. Klepper and Nagin acknowledge, however, that this result follows from the functional form of the detection probabilities and the assumption of risk-neutral taxpayers. In this paper, we consider the influence of attitudes toward risk (risk-aversion and risk-neutrality) and fixed and independent probabilities of detection on the optimal compliance behavior of taxpayers.

Two other papers consider multiple modes of tax evasion. Cremer and Gahvari (1994) derive optimal tax rules, and Cowell and Gordon (1995) derive optimal audit strategies. Clearly, all three perspectives are related to one another, but we adopt a slightly different perspective. We focus on the equilibrium behavior of the taxpayer.[5]

Generally speaking, the empirical literature also assumes a single mode of tax evasion. Klepper and Nagin (1989) and Feinstein (1991) are important exceptions that are discussed in greater detail below. There are four basic sources of data used by researchers to measure and study tax compliance: audit data, survey data, tax amnesty data, and data generated by laboratory experiments. In this study, we use data from the 1985 TCMP.

[5] There also is a substantial game-theoretic literature on tax compliance, with different types of taxpayers. Graetz, Reinganum and Wilde (1986) are the first to incorporate honest taxpayers into a game-theoretic framework. Erard and Feinstein (1994) show the importance of the presence of honest taxpayers in a model with income distributed along a continuum rather than discretely, as in the case of Graetz et. al. (1986). Reinganum and Wilde (1985) examine the case when the tax authority can commit to an audit rule. Sanchez and Sobel (1993) provide an excellent discussion of this type of model.

The household TCMP is a stratified random sample of federal individual income tax returns that are subject to thorough examination by experienced IRS tax examiners.[6]

Using the 1969 TCMP and assuming a single mode of tax evasion, Clotfelter (1983) finds that income and detection probabilities have a positive and statistically significant effect on income reporting compliance; while, the tax rate has a negative and statistically significant effect on compliance. Klepper and Nagin (1989) estimate separate equations for voluntary reporting percentages by line item using 1982 TCMP data aggregated by audit class. They include three classes of variables: (1) measures of the cost to the IRS of establishing the true amount on each line item; (2) measures of the complexity of the reporting rules pertaining to each line item; and (3) measures of the ambiguity of the legal requirements for each line item. These variables have the expected negative effect on line-item reporting compliance. Although their data do not permit them to control for income or marginal tax rates, they report evidence in support of the hypothesized substitution process for line item reporting compliance described above.

In a path breaking study, Feinstein (1991) estimates a model of fractional detection using pooled 1982 and 1985 TCMP data. In contrast to Clotfelter (1983), Feinstein finds that the tax rate has a positive and statistically significant effect on compliance in the pooled regressions, but income is not statistically significantly different from zero. In order to measure the scope for evasion on a particular return, Feinstein includes dummy variables for the presence of sole proprietorship income (Schedule C) and farm income (Schedule F). The idea being that it is more difficult for the IRS to

[6] The IRS conducted the first TCMP survey for tax year 1963, and has subsequently conducted the survey every three years through 1988. For most of those years, the surveys included between 45,000 and 55,000 households.

detect underreporting of these sources of income because they are not subject to third party reporting or withholding. As expected, these two variables have a negative and statistically significant effect on income reporting compliance.

Feinstein (1991) also estimates a disaggregated or multi-mode version of his partial detection model using the 1982 TCMP. This model consists of four equations: (1) an evasion equation for underreporting AGI; (2) an evasion equation for overstating deductions; (3) a detection equation for detecting underreported AGI; and (4) a detection equation for detecting overstated deductions. The stochastic disturbances are jointly normally distributed with correlation P_1 in the two evasion equations and jointly normally distributed with correlation P_2 in the two detection equations.[7] In this version of the model, he finds that income and the marginal tax rate have a negative and statistically significant effect on reporting compliance in both equations.

The empirical literature reports mixed finding on the role of marginal tax rates and income on reporting compliance.[8] However, there appears to be some consensus on the positive effect of lower costs of detection (diminished scope for evasion) on compliance. This conclusion appears to be robust to alternative econometric

[7] The correlation between the disturbances in the two evasion equations (P_1) is estimated to be 0.8 and 0.2 in the case of the correlation between the detection equations (P_2).

[8] For example, Alm et al. (1990) and Dubin and Wilde (1988) report a positive relationship between marginal tax rates and income reporting compliance; Feinstein (1991) reports mixed results; and Clotfelter (1983) and Joulfaian and Rider (1996, 1998) report a negative effect.

specifications, variable definitions, and data.[9] With the exception of Klepper and Nagin (1989) and Feinstein (1991), most of these studies do not allow us to draw conclusions about the effect of increased enforcement effort in settings with multiple modes of tax evasion. Our empirical approach focuses on these issues.

We also improve upon the work of Klepper and Nagin (1989) and Feinstein (1991). As previously noted, Klepper and Nagin use aggregate data and, thus, are unable to control for marginal tax rates and income. Omitting the marginal tax rate and income from the regression could lead to biased estimates if, as seems likely, audit probabilities are correlated with the omitted regressors. Since we use individual tax return data, we are able to control for the potential effect on compliance of tax rates and income. Although Feinstein (1991) makes a significant advance in the estimation of tax compliance models, his estimation method is computationally intensive. In order to make his model computationally feasible, he estimates the model on a relatively small number of returns (2,267). In contrast, we estimate our model on 42,811 returns and, by taking advantage of third party reporting of some line items, more carefully control for the risks of detection on a given return.

A Model of Multiple Modes of Tax Evasion

Our basic research question is whether increased enforcement effort in one mode of evasion has a positive effect on compliance in the targeted mode as well as others. We

[9] Experimental evidence based on a single mode of evasion also supports the conclusion that participants who have greater perceived opportunities for noncompliance tend to be significantly less compliant. See, for example, Robben et al. (1990).

address this issue by introducing a second mode of evasion into the Allingham and Sandmo (1972) and Yitzhaki's (1974) model of tax evasion.

We assume that individuals maximize expected utility (EU). Expected utility is a function of after-tax income (Y-T); where Y is lump-sum income and T is the true tax liability. We also assume that the utility function is a monotone increasing and concave function of after-tax income or $U' > 0$ and $U'' \leq 0$. In this framework, there are two ways that an individual can avoid reporting T. These are given by E_1 and E_2, where $0 \leq E_1 \leq T$, $0 \leq E_2 \leq T$ and $0 \leq E_1 + E_2 \leq T$.[10]

The probabilities of detection in modes 1 and 2 are denoted P_1 and P_2, respectively.[11] For the sake of simplicity, we assume that the detection probabilities are fixed and independent, or $\frac{\partial P_1}{\partial E_1} = \frac{\partial P_1}{\partial E_2} = \frac{\partial P_2}{\partial E_1} = \frac{\partial P_2}{\partial E_2} = 0$. In other words, the probabilities of detection are independent of both the level of evasion in the targeted mode as well as the level of evasion in the other mode. Although this assumption does not describe the entire array of enforcement strategies employed by the IRS, this assumption does capture essential features of the IRS's information returns processing program (IRP), which is by far their most cost effective tax enforcement program. Briefly, the IRP program consists of using high speed computers to match nearly one billion third party reports of income

[10]The assumption that 0#E_i#T for *i*=(1, 2) is not required. In fact, individuals may want to exaggerate liability in one mode and understate liability in another in order to reduce the risk of detection. Nevertheless, this assumption is useful for interpreting the comparative-static results.

[11]A detection probability is a compound event. Specifically, there is a probabilistic event that a return, or line item, will be selected for review. Conditional on being selected, some or all of the misreporting may be uncovered. For simplicity's sake, we assume all evasion is uncovered if a return (line item) is selected for review.

and deductions to over one hundred million individual income tax returns.[12] The match allows the IRS to identify anomalous reports of line items subject to third party reporting, such as wage and salary income, and issue tax assessments based on these anomalies. For cost reasons the IRS does not issue assessments for all anomalous reports identified by IRP. Furthermore, the probabilities of detecting misstatements on line items covered by third party reports are independent of any misreporting on other line items. In short, we believe that the assumption of fixed and independent detection probabilities reflect essential features of the IRP program.[13] Following Yitzhaki (1974), we assume that taxpayers must pay a penalty that is proportional to the unreported tax liability that is detected. Specifically, the payment for detection in mode 1 is equal to the unreported tax liability (E_1) and a penalty $(\theta_1 E_1)$, or $(1+\theta_1)E_1$, where θ_1 is the penalty rate in mode 1. Likewise, a taxpayer detected avoiding tax in the second 2 must pay $(1+\theta_2)E_2$. To induce a mixed strategy, $E_1 > 0$ and $E_2 > 0$, we assume that $P_1 < P_2$ and $\theta_1 > \theta_2$.

If both modes of evasion are used, there are four possible outcomes: (1) evasion is not detected in either mode, with probability $(1-P_1)(1-P_2)$; (2) evasion is detected in both modes, with probability $P_1 P_2$; (3) and (4) evasion is detected in one mode but not the

[12] In tax year 1985, the tax year from which our data are drawn, the IRS required third party reporting of wage and salary income (IRS Form W2), interest and dividend income (IRS Form 1099), home mortgage interest income, and state and local taxes, the latter two being deductions on Schedule A of IRS Form 1040.

[13] Obviously, this assumption does not completely describe the various enforcement strategies employed by the IRS, particularly special audits and field audits. Martinez-Vazquez and Rider (1995) examine alternative enforcement strategies, assuming multiple modes of tax evasion. He finds that the effect of increased enforcement effort is ambiguous in both modes: the targeted mode as well as the other one.

other, with probabilities $(1-P_1)P_2$ and $(1-P_2)P_1$, respectively. Accordingly, expected utility (EU) can be written as follows:

$$\mathrm{EU} = (1-\mathrm{P}_1)[(1-\mathrm{P}_2)\mathrm{U}(\mathrm{Z}_1) + \mathrm{P}_2\mathrm{U}(\mathrm{Z}_2)] + \mathrm{P}_1[(1-\mathrm{P}_2)\mathrm{U}(\mathrm{Z}_3) + \mathrm{P}_2\mathrm{U}(\mathrm{Z}_4)] \tag{1}$$

where $Z_1 = Y - T + E_1 + E_2; Z_2 = Y - T + E_1 - \theta_2 E_2; Z_3 = Y - T - \theta_1 E_1 + E_2$; and $Z_4 = Y - T - \theta_1 E_1 - \theta_2 E_2$. In the following discussion, we assume that an interior solution $(E_1 > 0$ and $E_2 > 0)$ always exists. Assuming the probabilities of detection are fixed and independent, the first-order conditions (FOC) of an interior maximum of (1) are given by

$$\frac{\partial \mathrm{EU}}{\partial \mathrm{E}_1} = (1-\mathrm{P}_1)[(1-\mathrm{P}_2)\mathrm{U}'(\mathrm{Z}_1) - \mathrm{P}_2\mathrm{U}'(\mathrm{Z}_2)] + \mathrm{P}_1[(1-\mathrm{P}_2)\mathrm{U}'(\mathrm{Z}_3) - \mathrm{P}_2\theta_1\mathrm{U}'(\mathrm{Z}_4) = 0 \tag{2}$$

$$\frac{\partial \mathrm{EU}}{\partial \mathrm{E}_2} = (1-\mathrm{P}_1)[(1-\mathrm{P}_2)\mathrm{U}'(\mathrm{Z}_1) - \mathrm{P}_2\theta_2\mathrm{U}'(\mathrm{Z}_2)] + \mathrm{P}_1[(1-\mathrm{P}_2)\mathrm{U}'(\mathrm{Z}_3) - \mathrm{P}_2\theta_2\mathrm{U}'(\mathrm{Z}_4)] = 0 \tag{3}$$

We assume that the second-order conditions (see equations 4-6 in the Appendix) are satisfied by the concavity of the utility and detection probability functions. Our major findings are discussed below; proofs are provided in the Appendix for the interested reader.

Proposition 1(a): Assuming risk-aversion and fixed and independent detection probabilities, the effect of an increase in the detection probability in a given mode has an ambiguous effect on evasion in both modes.

In other words, we cannot predict how an increase in a detection probability will effect compliance in the targeted mode, much less the other mode. Similar results obtain for a change in the probability of detection in the other mode.

Proposition 2(a): Assuming risk-aversion and fixed and independent probabilities of detection, the effect of an increase in the penalty of a given mode has an ambiguous effect on evasion in both modes.

Again, it is not possible to predict whether a taxpayer responds to an increase in a penalty rate in a given mode by decreasing, leaving unchanged, or increasing their evasion in either mode.

In contrast to the findings reported above, Allingham and Sandmo (1972) and Yitzhaki (1974) find that increasing the risk of detection by either increasing the probability of detection or increasing the penalty has a positive effect on income reporting compliance in the context of a single mode of tax evasion. In the Allingham-Sandmo-Yitzhaki single-mode model, increasing the risk of detection leads to an increase in income reporting compliance to reduce the attendant risk. In the multiple modes case, however, there are multiple offsetting effects from increasing the risk of detection. As in the Allingham-Sandmo-Yitzhaki model, increasing the risk of detection reduces evasion in both modes to reduce overall risk, but there also is substitution away from the targeted mode and into the untargeted mode due to the change in relative risk among the modes. By definition, the latter response is not available in the single mode case. Depending upon the strength of the latter effect, the resulting increase (decrease) in expected after-tax income, assuming decreasing absolute risk aversion, may lead to a decrease (increase) in compliance in the targeted mode. Hence the offsetting nature of these multiple effects implies that the effect of increased enforcement effort in a given mode has an ambiguous effect on evasion in both modes, which is consist with the ambiguous results in the multiple modes case. [1]

[1] How much evasion changes in each of the two modes will depend on a number of parameters including how close substitutes the two modes are, the initial levels of evasion in each mode, or increasing or decreasing risk aversion in the individual's preference.

We also derive results in the case of risk-neutral taxpayers. Briefly, when we assume risk neutrality, we find that increasing the detection probability in a given mode has no effect on evasion in either mode; whereas, increasing the penalty in a given mode also has an ambiguous effect on both modes. These results are summarized in Table 1.

Ideally, we would like to know the net-revenue effect of increased enforcement effort in a given mode: whether increased enforcement effort targeting a given mode leads to an increase or decrease in tax revenue. This depends on the third derivatives of the utility function. Unfortunately, we do not even know the signs of these derivatives, much less their relative magnitudes. Therefore, we turn to our empirical work to gain greater insight into this important issue.

A Preliminary Look at the Data

We would like to know whether taxpayers perceive alternative modes as substitutes or complements. Also, we would like to know whether in the presence of multiple modes of tax evasion stricter enforcement actually leads to lower evasion. To this end, we use the IRS's 1985 TCMP, which is a stratified random sample consisting of approximately 49,162 federal individual tax returns that are subjected to thorough line-by-line review by experienced IRS tax examiners. The 1985 TCMP records the taxpayer's report and the examiner's correction for most line-items on the return and accompanying schedules, providing extremely detailed information about noncompliance for tax year 1985.[14]

[14]There are three shortcomings of TCMP data. First, since the TCMP sample is drawn from tax filers, the data do not provide information on non-filers. Second, tax

We make the following restrictions on the sample. We exclude taxpayers in the credit range of the earned income tax credit (EITC). In contrast to taxpayers facing positive marginal tax rates, taxpayers in the credit range of the EITC face negative marginal rates and, therefore, have an incentive to overstate taxable income in order to claim a larger credit.[15] For reasons related to the empirical specification, described in greater detail below, we also eliminate returns with negative adjusted gross income (AGI), as reported by the taxpayer and corrected upon audit. Since married taxpayers filing jointly are subject to a different tax rate schedule than single taxpayers; we also eliminate returns in which the auditor-adjusted filing status differs from the reported one. The resulting sample consists of 42,811 returns.

As a first step, we examine our data for evidence of multiple modes of tax evasion by sorting our sample into returns that understate, honestly, and overstate income and deductions.[16] Thus, there are nine strategies: (1) accurately report income and deductions; (2) accurately report income and exaggerate deductions; (3) accurately report income and understate deductions; (4) understate income and deductions; (5) understate income and

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returns typically lack detailed information on demographic factors that may influence tax compliance behavior. Friedland, Maital, and Rutenberg (1978), Witte and Woodbury (1983), Baldry (1987), Dubin and Wilde (1988), and Beron, Tauchen, and Witte (1992) have examined the role of a variety of demographic variables on tax compliance, including age, race, and education, among others. Third, it is well known that the TCMP fails to detect potentially significant amounts of underreported income, particularly income from sources that are not subject to third party reporting. Despite these shortcomings, TCMP data are widely regarded to be the best source of data available on tax noncompliance.

[15]See Joulfaian and Rider (1996) for an examination of the compliance effects of the EITC.

[16] Recall that the theoretical model was restricted for convenience of interpreting results by assuming taxpayers do not understate deductions or overstate income.

accurately report deductions; (6) understate income and exaggerate deductions; (7) exaggerate income and deductions; (8) exaggerate income and accurately report deductions; and (9) exaggerate income and understate deductions. Strategies 2, 4, 5, 6, and 9 are consistent with understating taxable income – AGI less itemized (standard) deductions; the others are not. We refer to strategies 2 and 5 as pure strategies, and strategies 4, 6, and 9 as mixed strategies.

The results for the full sample are summarized in Table 2A. For example, the cell in the third row and third column shows that 41 percent of the returns in our sample that understate income also exaggerate deductions. For this subset of returns, the average understatement of income is $3,603, and the average overstatement of deductions is $1,647. Consequently, taxable income is understated by an average of $5,250 [= -$3,603-$1,647], and average auditor-adjusted AGI for these returns is $65,402. The cell in the third row and last column shows that 46 percent of all returns understate total income. Conditional on understating income, the average understatement is $3,265; deductions are exaggerated by an average of $411; the average understatement of taxable income is $3,677; and the average auditor-adjusted AGI for this sub-sample is $54,777.

Table 2A provides ample evidence of multiple modes of tax evasion.[17]

[17]We cannot assume that all reporting errors are deliberate. After all, some taxpayers have apparently overstated taxable income, which one would assume, in many cases, reflect honest mistakes. If all overstatements of taxable income are honest, then it seems reasonable to assume that reporting errors would be symmetric about zero. It is clear from examination of Table 2A that more taxpayers understate taxable income than overstate it, and they do so in larger average amounts. Thus, it seems reasonable to conclude that at least some reporting errors are intentional. Nevertheless, some reporting errors, even those dramatically in the taxpayers favor, may reflect honest mistakes.

Approximately 24 percent (0.62*0.38) of returns honestly report taxable income; 63 percent understate taxable income; and the remaining 13 percent overstate taxable income. Of the 63 percent that understate taxable income, approximately 57 percent – 36 percent of all returns – use a mixed strategy or multiple modes of tax evasion. Two of the three mixed strategies are consistent with understating taxable income, and, in these cases, the average understatement exceeds that for pure strategies.

To gauge the impact that information reporting and withholding have on reporting compliance, we split our sample into returns with auditor-adjusted non-wage income exceeding 25 percent of auditor-adjusted total income (returns with "significant business income") and those with auditor-adjusted wage and salary income exceeding 75 percent (returns with "primarily wage income"). The results of the former are reported in Table 2B and the latter in Table 2C.

As the row 3 totals of Tables 2B and 2C show, returns with significant income from non-wage sources are more likely to understate income than those with primarily wage income, 52 percent versus 43 percent, respectively. Furthermore, returns with significant non-wage income understate taxable income more intensively, than their wage income counterparts. This is true in absolute terms ($5,350 versus $2,330) and as a fraction of AGI (9.2 percent versus 4.5 percent of auditor-adjusted AGI). In contrast, returns with primarily wage income are more likely to overstate deductions than those with significant non-wage income, 39 percent versus 32 percent, respectively. Despite the greater propensity of wage earners to employ the deductions mode, returns with significant non-wage income, conditional on exaggerating deductions, understate taxable income by a greater average amount in absolute terms and as a fraction of auditor-adjusted AGI.

Empirical Analysis

Tables 2A through C provide clear evidence that taxpayers use multiple modes of tax evasion and seem to do so in a manner consistent with economic intuition. Nevertheless, many interesting questions remain unanswered. For example, we would like to know whether increasing the detection probability in a given mode increases compliance in the targeted mode and by how much the other mode is affected. To address this issue, we turn to our multivariate analysis.

The Empirical Model

To begin disentangling the effects of tax enforcement policies in a multi-mode tax evasion context, we assume that there are two potential modes of tax evasion: (1) total income reporting compliance and (2) deductions and adjustments reporting compliance. In our theoretical model, we also assume two modes of evasion, and the model predicts that increased enforcement effort in one mode influences compliance in both modes. Consequently, in our empirical model we assume that compliance in the two modes are simultaneous.

Accordingly, we assume taxpayer i's income reporting compliance, denoted y_{ij}, depends upon a vector of explanatory variables, X_{ij}, and taxpayer i's deductions and adjustments reporting compliance, denoted y_{ik}. Likewise, taxpayer i's rate of deductions reporting compliance depends upon a similar, though not identical, vector of explanatory variables, denoted X_{ik}, and taxpayer i's rate of income reporting compliance. These relationships can be summarized as follows:

$$y_{ij} = X'_{ij} B_j + \pi_j y_{ik} + \in_{ij} \tag{4}$$

$$y_{ik} = X'_{ik} B_k + \pi_k y_{ij} + \in_{ik} \tag{5}$$

We assume the error terms $\in_{ij}$ and $\in_{ik}$ have zero mean and finite variance.[18] Feinstein's (1991) disaggregated partial-detection model has some advantages over our empirical specification. In particular, our specification assumes complete and uniform detection across returns. Feinstein (1991) provides convincing evidence that this assumption may not be valid. On the other hand, he does not report very much evidence of serious bias resulting from the failure to account for fractional detection.[19] Furthermore, and as previously noted, he limits his sample to four IRS districts or 2,267 returns. Our specification is more flexible and allows us to estimate the model on a larger number of returns (42,811). We believe our approach has advantages that recommend it at this stage of model development.

Our empirical model employs variables commonly used in the tax evasion literature. These include the last-dollar marginal tax rate in each mode of evasion, total

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[18] It is evident from Table 2A that the dependent variable is not symmetrically distributed. In fact, the data are highly skewed. Thus, we cannot assume that the errors are normally distributed. Since we have a rather large sample, we invoke the usual assumption that the t-ratios are asymptotically normally distributed. Given the skewness of the data, future work should explore econometric techniques that depend on the median as the measure of central tendency rather than the mean.

[19] The one exception may be the effect of marginal tax rates on compliance. While others find that marginal tax rates have a negative effect on compliance, he reports a positive effect, at least in the case of the pooled sample. Joulfaian and Rider (1998) show that whether SECA taxes are accounted for in the marginal tax rate can explain such contradictory results.

pre-tax income, proxies for probabilities of detection in each mode, and certain demographic information.[20] In order to identify the parameters, B_j, B_k, π_j, and π_k, of the model, we need at least one variable unique to equation 1 and one unique to equation 2. Accordingly, we assume the detection probabilities in mode j are unique to equation 1, and the detection probabilities in mode k are unique to equation 2. In addition, the last-dollar marginal tax rate is likely to be endogenous as well.[21] As described in greater detail below, we employ the first-dollar marginal tax rate as an instrumental variable for the potentially endogenous last-dollar rate.[22]

Construction of the Variables

The following is a brief description of the construction of these variables. Column 1 of Table 3 provides summary statistics for the variables used in this study.

Dependent Variables

The log of the income gap is the natural logarithm of the maximum of 1.0 and reported total income less auditor-adjusted total income. Total income includes wages, net business income from Schedule C (Sole Proprietorship), F (Farm), and E (Partnership, S-Corporation, and rental income) activities; capital gains and interest; and

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[20] Note the lack of variation in the statutory penalty rate schedule does not permit us to estimate the effect of penalty rates on compliance. However, it is possible to use an experimental approach to examine this issue in the context of multiple modes of tax evasion. See, for example, Cummings et al. (2001).

[21]Identifying the tax price (see Feenberg, 1987) is always a concern with cross-sectional data. Although more recent TCMP data are available, we have therefore decided to use the 1985 TCMP because there is more cross-sectional variation in the tax price in pre-TRA 1986 data.

[22]First-dollar marginal tax rates are obtained using auditor-adjusted data. Last-dollar marginal tax rates are calculated with taxpayer-reported data.

interest and dividend income, among others, less certain non-taxable sources, such as excluded dividends and capital gains

The log of the deductions and adjustments gap is the natural logarithm of the maximum of 1.0 and auditor-adjusted deductions and adjustments less taxpayer-reported deductions and adjustments. Deductions and adjustments include exemptions for self, spouse, and dependent children; adjustments; and itemized deductions or, as the case may be, the standard deduction(s). As reported in Table 3, the average values for the log of the income and deductions gaps are 3.3831 and 2.0926, respectively.

The log of the income (deductions) gap is widely adopted in the empirical literature, but, in the context of this study, there are some drawbacks to this specification. Specifically, the logarithmic specification masks some legitimate tax evasion strategies.[23] Nevertheless, the double-log specification allows for potential non-linear effects and allows us to compare our results to those in the literature. Since the data are truncated at zero, we estimate the model using Two-Stage Tobit (2ST).

Independent Variables

Log of total income is defined as the natural logarithm of auditor-adjusted, pre-tax, total income. As previously noted, total income includes wages, net business income from Schedule C, E, and F activities; capital gains (taxable and non-taxable); interest and

[23]Since the logarithm of non-positive values does not exist, it is necessary to set such values equal to 1.0 before taking the logarithm. In particular, cases in which taxable income is overstated are set equal to zero and, therefore, appear to be compliant, however, such cases are presumably the result of honest mistakes. Assuming honest mistakes are white noise errors, truncating the data in this fashion means that all understatements of taxable income are treated as deliberate, when, in fact, some may be the result of honest mistakes. This approach obscures sophisticated evasion strategies, such as understating income and deductions or overstating income and deductions.

dividend income (taxable and non-taxable); and other miscellaneous sources. In our sample, average, auditor-adjusted, pre-tax income is equal to approximately $62,407.

The log of the last-dollar tax price is the natural logarithm of one (1.0) minus the last-dollar marginal tax rate. The last-dollar marginal tax rate is calculated using data as reported by the taxpayer.[24] We believe that the theoretically appropriate marginal tax rate for decision-making is the last-dollar rate which includes the effect of any anticipated evasion activities undertaken by the taxpayer. Thus, the last-dollar tax rate is potentially endogenous. The first-dollar marginal tax rate excludes the effect of any tax evasion activities. Therefore, the first-dollar rate is exogenous and, consequently, a proper instrument for the last-dollar rate. A number of features of the tax code, such as the phase-out range of the earned income tax credit and the self-employment tax, drive a wedge between the marginal tax rate on income and deductions. Accordingly, we compute two variants of the first- and last-dollar marginal tax rates: (1) an income variant by adding one hundred dollars to wage income and (2) a deductions variant by adding one hundred dollars to itemized deductions. As shown in Table 3, the average of the log of last-dollar income tax price in our sample is -0.344 and -0.259 in the case of deductions.

[24] A detailed tax calculator is used to construct the marginal tax rates. The calculator accounts for both the statutory rate schedule and many implicit tax rates that arise from special features of the tax code. Last-dollar marginal rates are obtained by adding one hundred dollars to reported wages (charitable contributions). First-dollar marginal rates are calculated by adding one hundred dollars to auditor-adjusted wage income (charitable contributions).

Scope for misreporting tax attributes

We also require measures for the perceived risk of detection in each mode. But, the preferred measure, the subjective probability of detection in each mode, is inherently unobservable. Many researchers have struggled with the difficulty of finding appropriate proxies for detection probabilities when estimating income reporting compliance equations. We face the added burden of developing probabilities of detection for two modes of evasion. At first blush, objective audit probabilities would seem to be good candidates for the perceived detection probability. Unfortunately, information on objective audit probabilities are closely held by the IRS. Furthermore, objective audit probabilities are often a function of reported tax attributes, particularly in the case of field audits and, as such, are likely to be endogenous. For example, if taxpayers believe that the tax authority audits taxpayers with unusually high ratios of itemized deductions relative to reported AGI, then taxpayers that dramatically underreport income may choose not to report some valid deductions in order to reduce the probability of detection.

Rather than use objective audit probabilities, researchers have tended to use proxy variables that measure the scope for tax evasion on a return. Since wage income is subject to third party reporting and withholding, taxpayers with a lower share of wages in AGI have a greater scope for understating income and a lower attendant probability of detection than those with higher shares. As such reasoning suggests, the IRS estimates that upwards of 98 percent of wage income is voluntarily reported for federal income tax purposes and much lower rates for business income, which is often not subject to third party reporting.[25] By extending this reasoning to include other line items that are subject to third party reporting, we develop additional measures of the scope for evasion on a return. More specifically, since interest and dividend income, deductions for home mortgage interest, and state and local taxes, as well as wage and salary income, are subject to third party reporting, we construct the following three proxies for the scope for tax evasion on a given return.

Wage share is the ratio of auditor-adjusted wages and auditor-adjusted total income from taxable sources.

Interest-and-dividend share is the ratio of auditor-adjusted interest and taxable dividends and auditor-adjusted total income from taxable sources.

Itemized deductions share is the sum of auditor-adjusted deductions for home mortgage interest and state and local taxes as a proportion of auditor-adjusted total itemized deductions. If the taxpayer does not itemize, then this value is set equal to zero. Thus, by construction, it also distinguishes between itemizers and non-itemizers. Clearly, itemizers have a greater scope to misreport deductions with a lower attendant risk of detection than do non-itemizers.[26]

The wage and interest-and-dividend shares serve as proxies for the scope of evasion in the income reporting compliance equation; while, the itemized deductions share performs this role in the deductions reporting compliance equation. Since wages and salary also are subject to withholding, while interest and dividends are not, we allow

[25]See, for example, Clotfelter (1983) and Joulfaian and Rider (1996).

[26]Note that non-itemizers can still exaggerate exemptions, adjustments, and the number of standard deductions.

them to have different effects on compliance by entering them separately into the income reporting compliance equation. As shown in Table 1, wage income is approximately 67 percent of auditor-adjusted total income, while interest and dividends constitute 15.4 percent. The deductions for home mortgage interest and state and local taxes are nearly 23 percent of auditor-adjusted itemized deductions and adjustments.

In addition, we include dummy variables for the presence of Schedule C (31.4 percent of the sample), Schedule F (9.5 percent), rental income (24.9 percent), partnership income (18.3 percent), and itemized deductions (58.6 percent). Since these sources of income are not subject to third party reporting, there is a greater scope to misreport these sources of income and, therefore, serve as suitable proxies for the probability of detection or the scope for misreporting income.

Demographic variables

In order to control for differing attitudes toward risk and tastes for evasion, we use three demographic variables that have been shown in the literature to influence tax compliance behavior.[28] These include an indicator variable for marital status (single versus married) and the number of dependents (family size). We also include the age of the primary taxpayer and age-squared to account for any non-linearity in this variable.[29]

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[28] Witte and Woodbury (1985), Beron, Tauchen and Witte (1992), and Dubin and Wilde (1988) analyzed data provided by the IRS that links 1969 TCMP data, aggregated to the three-digit zip code level, with census and IRS enforcement data. These studies show that age, marital status, race, and education are important determinants of compliance.

[29] Although taxpayers do not report their age on the tax form, we are able to obtain the necessary information to calculate the age of the primary filer from social security records.

As shown in Table 3, approximately 69.3 percent of the observations in our sample are married; the average number of dependents is 2.6, and the average age of our sample is approximately 46 years old.

Empirical Results

Now, we turn to a discussion of our 2ST estimates, on our sample of 42,811 returns. We present both independent and simultaneous estimates of both equations. Specifically, the estimated coefficients from the independent estimation of the log of the income and deductions gap equations are reported in columns 2 and 3 of Table 3, respectively, and the simultaneous estimates are reported in columns 4 and 5, respectively. The independent equations are also estimated by 2ST due to the potential endogeneity of the last-dollar tax price.

We begin with a description of the most intriguing results from the simultaneous estimates: how does compliance in one mode affect compliance in the other mode. In the income gap equation (column 4), the estimated coefficient of the (log) deductions gap is equal to -0.134 and statistically significant. Thus, increasing deductions reporting compliance has a negative effect on income reporting compliance. Likewise, the estimated coefficient of the log of the income gap in the deductions gap equation (column 5) is equal to -0.017 and statistically significant.

Taken together these estimates suggest that income and deductions reporting compliance are substitute modes of evasion. In other words, enforcement strategies that increase revenue through increased reporting compliance in one mode result in a (partially) offsetting reduction in revenue from deteriorating compliance in the other mode.

Focusing on the estimates for the log of the income gap equation, the log of the tax price is negative and statistically significant. This implies that increasing the marginal tax rate (decreasing the tax price) leads to a decrease in income reporting compliance. This is consistent with much of the empirical literature. The estimated coefficient of the log of total income is negative and statistically significant. In other words, there is an inverse relationship between income and income reporting compliance. This estimate is at odds with the widely held belief that risk aversion is decreasing in income, which would imply a positive coefficient. It is also somewhat at odds with much of the empirical work as well.[30] But, it is interesting to note that we also get a negative and statistically significant estimated coefficient for the log of total income in the independent case (column 1). So, the sign of this estimate does not appear to be simply an artifact of the simultaneous specification.

In addition to the deductions gap variable discussed above, the wage share and interest-and-dividend share serve as proxies for the probability of detecting income misreporting. The estimated coefficients for these variables are negative and statistically significant. In other words, increasing the share of income subject to third party reporting reduces the scope for misreporting and, therefore, increases compliance. This is consistent with previous research and economic intuition.

We also include a set of indicator variables for different types of business income, which are not subject to third party reporting or withholding. The indicator variables for sole proprietorship, farm, and rental income are positive and, with the exception of farm

[30]Clotfelter (1983) also obtains a negative and statistically significant estimates in some audit classes; while, Feinstein (1991) reports a positive though statistically insignificant estimate in the pooled regressions.

income, statistically significant. But, the indicator variable for partnership income is negative and statistically significant. Since a partnership is a pass through entity for tax purposes, misreporting partnership income requires collusion among all the partners. The difficulties and risks of forming such conspiracies may explain the negative coefficient. In any event, these variables have the expected signs and are consistent with much of the literature.

Furthermore, the estimated coefficients on married, number of dependents, and age are positive and statistically significant; while, the estimated coefficient of age-squared is negative and statistically significant. The combined effect of these two terms is positive for age less than 46 and negative otherwise. Thus, married taxpayers, taxpayers with dependents and older taxpayers are less compliant. Again, this is generally consistent with results reported in previous studies. Finally, the simultaneous estimates (column two) from the income gap equation are completely consistent with the independent estimates (column one). This is somewhat reassuring in that neglecting the simultaneity between the two modes of evasion does not appear to seriously bias the estimates.

Turning to the estimates from the log of deductions gap equation, the results are very similar to those obtained for the income gap equation. Specifically, the log of the tax price and log of total income have a negative and statistically significant effect on deductions reporting compliance. Though marital status and number of dependents are positive, they are statistically insignificant. As in the income gap equation, age and age-squared are positive and negative, respectively, and both are statistically significant. The combined effect of these two terms is positive for age less 48 and negative otherwise.

Itemizer status, like the business income indicator variables in the income gap equation, serves as a proxy for the scope for misreporting deductions. In other words, there is greater scope to misreport deductions when the taxpayer itemizes. As one would expect, the estimated coefficient on this variable is positive and statistically significant.

Surprisingly, the estimated coefficient on deductions share is positive and statistically significant. In other words, there is an inverse relationship between the share of itemized deductions and the deductions reporting compliance. Although this does not contradict the theory, it seems premature to conclude, as this estimate suggests, that increasing the probability of detecting exaggerated decreases deductions reporting compliance and increases income reporting compliance. Again, the simultaneous estimates, discussed above and reported in column 5, are consistent with the independent estimates reported in column 3 of Table 3.

To test the robustness of the results reported in columns 4 and 5 of Table 3, we stratify the sample into three audit classes, defined by total positive income and other criteria thought by the IRS to reflect evasion probabilities, and re-estimate equations 4 and 5. The results and the descriptive statistics for these sub-samples are reported in Table 4. Examining the descriptive statistics in columns 1, 4, and 7 provides some insights into the differences in the sub-samples. For example, audit classes 1 and 2 have much higher values for wage-share, 73.3 and 84.2 percent, respectively, than audit class 3 (31.1 percent). On the other hand, audit classes 2 and 3 have a much higher proportion of itemizers, 93.6 and 56.7 percent, respectively, than audit class 1 (28.6 percent). Furthermore, audit class 3 has a much higher proportion of Schedule C filers, 77.8

percent, than audit classes 1 and 2. Finally, it is worth noting that log of the last-dollar tax prices are significantly larger for audit class 2 than for the other two.

The estimated results reported in Table 4 are generally consistent with those reported in Table 3. The log of the income gap is negative and statistically significant in the deductions gap equations (columns 3, 6, and 9) for audit class 2 (column 6), positive and statistically significant for audit class 3 (column 9), and statistically insignificant in audit class 1. Similarly, the log of the deductions gap in the income gap equation (columns 1, 4, and 8), it is negative and statistically significant for audit classes 2 and 3, and positive and statistically significant in audit class 1. The log of the tax-price is negative and statistically significant in 4 out of 6 cases. The estimated coefficients for the variables that measure the scope for evasion in each mode have the anticipated signs and are statistically significant. More specifically, the estimated coefficients of wage-share and interest-share are negative and statistically significant for audit classes 1 and 2. As in Table 3, however, the estimated coefficient on the deductions share is positive and statistically significant for audit classes 2 and 3. Likewise, the dummy variables for business income are generally positive and statistically significant, except for partnership income (PSP), which is either negative and statistically significant, as in Table 3, or statistically insignificant.

In conclusion, it is interesting to note that for audit classes 1 and 2, in which the wage-share is relatively high, the mean of the log of the income gap tends to be rather small. In contrast, for audit class 2, in which the proportion of itemizers is much higher by comparison, the mean of the log of the deductions gap is larger. Thus, there seems to be strong evidence that multiple modes of tax evasion play a potentially important role in understanding the compliance behavior of taxpayers.

The Implications of Our Results for Tax Enforcement

We began this study by noting that multiple modes of tax evasion complicate the task of tax administration. For example, increasing compliance in one mode may be more than offset by deteriorating compliance in the other mode. Theoretically we find that there is no reason, *a priori*, to suppose that increasing detection probabilities and penalties will increase compliance in the targeted mode. Our empirical results suggest that taxpayers treat alternative modes of evasion as substitutes. In other words, while increasing the probability of detection in one mode increases compliance in the targeted mode, there will be deteriorating compliance in the other mode. But, the net-effect on taxable income reporting compliance of increases enforcement effort, and therefore the net tax revenue effect, is uncertain.

In order to address this final issue, we use our empirical model to simulate two alternative enforcement strategies. First, we change the share of wages subject to third party reporting and withholding by ten percent relative to the mean values of our data. This policy change leads to a 1.8 percent increase in income reporting compliance and a 0.1 percent decrease in deductions reporting compliance. Consequently, the net effect of a ten percent increase in covered wages is a 1.1 percent increase in taxable income reporting compliance.

Second, we consider the effect on compliance of changing a taxpayer from an itemizer to one that simply claims the standard deduction. This simulation is conducted by evaluating both estimated equations at the mean values of our data, with the itemizer dummy variable set equal to 1.0. We compare the resulting predictions with those obtained when we set the itemizer dummy variable equal to zero. The impact of this strategy is quite dramatic. The deductions gap is eliminated for all practical purposes, while the income gap increases by ten percent. The net effect of this policy change is a 40 percent increase in taxable income reporting compliance.

Thus we can conclude that the overall response to an increase in enforcement effort via an increase in the probability of detection or decrease in the opportunity to misreport a line item(s) leads to an increase in overall compliance. Of course, the estimated model can be used for many other policy simulations.

Conclusion

In this paper, we examine the theoretical and empirical implications of accounting for multiple modes of tax evasion on optimal taxpayer compliance behavior. Assuming risk-averse taxpayers and fixed and independent detection probabilities, we find that the effect of increasing the detection probability (or the penalty rate) in a given mode has ambiguous effects on compliance in both modes. We attempt to resolve this ambiguity by simultaneously estimating a model with two modes of tax evasion: income reporting compliance and deductions reporting compliance.

Three results are worth noting. First, we find evidence that income and deductions reporting compliance are substitutes. In other words, increased enforcement effort in a given mode increases compliance in the targeted mode, but is (partially) offset by deteriorating compliance in the other mode. Second, our estimates suggest that there is a negative relationship between the tax rate and income (deductions) reporting compliance and a positive relationship for third party reporting. Finally, we use our estimates to simulate two enforcement strategies: increasing the share of income subject to third party reporting and withholding and eliminating itemized deductions. Both policies lead to substantial increases in taxable income reporting compliance, however, eliminating itemized deductions appears to be particularly effective at increasing compliance. In part due to features of the data (i.e., lack of variation in the penalty rate), our empirical analysis addresses only some of the issues raised in the theoretical section. Given the potential significant implications of recognizing multiple modes of tax evasion on tax enforcement strategies, there is a need for further research in this area.

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Tables and Appendix

TABLE 1
Summary of Comparative-Static Results

Fixed and Independent Probabilities of Detection		Policy Parameters			
		ΔP_1	ΔP_2	$\Delta \Theta_2$	$\Delta \Theta_2$
$U'' < 0$ (risk averse)	Δ E_1	?	?	?	?
	Δ E_2	?	?	?	?
$U'' = 0$ (risk neutral)	Δ E_1	0	0	0	0
	Δ E_2	0	0	0	0

Note: We assume that $\theta_1 > \theta_2$, $P_1 < P_2$, $E_1 > 0$ and $E_2 > 0$.
+ (-): indicates a positive (inverse) relationship between the associated variables.
?: indicates an ambiguous effect between the associated variables.

TABLE 2A

Cross-Tabulation by Compliance Status

Full Sample

Total Income	Itemized Deductions + Adjustments			
Over State	**Under State**	**Honest**	**Over State**	**Row Totals**
Percentage	20%	37%	43%	16%
Income gap[a]	$1,812	$730	$1,186	$1,145
Deductions gap[b]	-$754	$0	$1,276	$400
Taxable Income gap[c]	$2,566	$730	-$90	$745
AGI[d]	$55,793	$34,085	$64,325	$51,539
Honest				
Percentage	11%	62%	27%	38%
Income gap	$0	$0	$0	$0
Deductions gap	-$633	$0	$1,248	$274
Taxable Income gap	$633	$0	-$1,248	-$274
AGI	$52,005	$29,340	$55,768	$39,015
Under State				
Percentage	22%	37%	41%	46%
Income gap	-$4,178	-$2,362	-$3,603	-$3,265
Deductions gap	-$1,230	$0	$1,647	$411
Taxable Income gap	-$2,948	-$2,362	-$5,250	-$3,677
AGI	$61,397	$39,192	$65,402	$54,777
Column Totals				
Percentage	17%	46%	36%	100%
Income gap	-$3,121	-$1,318	-$2,670	-$2,120
Deductions gap	-$2,813	$0	$4,333	$1,086
Taxable Income gap	-$308	-$1,318	-$7,003	-$3,206
AGI	$58,151	$33,587	$62,443	$48,298

NOTES:

[a]Income gap equals reported total income less corrected total income.

[b]Deductions gap equals reported deductions (+ adjustments) less corrected deductions (+ adjustments).

[c]Taxable income gap equals reported taxable income less corrected taxable income.

[d]AGI equals total income less adjustments.

TABLE 2B

Cross-Tabulation by Compliance Status

Significant Business Income

Total Income	Itemized Deductions + Adjustments			
Over State	**Under State**	**Honest**	**Over State**	**Row Totals**
Percentage	20%	44%	36%	17%
Income gap[a]	$2,797	$1,003	$1,587	$1,572
Deductions gap[b]	-$963	$0	$1,458	$330
Taxable Income gap[c]	$3,759	$1,003	$129	$1,242
AGI[d]	$52,992	$38,488	$70,756	$52,959
Honest				
Percentage	13%	64%	23%	31%
Income gap	$0	$0	$0	$0
Deductions gap	-$717	$0	$1,341	$222
Taxable Income gap	$717	$0	-$1,341	-$222
AGI	$51,058	$33,440	$56,317	$41,021
Under State				
Percentage	22%	43%	35%	52%
Income gap	-$6,250	-$3,668	-$6,432	-$5,205
Deductions gap	-$1,646	$0	$1,431	$145
Taxable Income gap	-$4,604	-$3,668	-$7,863	-$5,350
AGI	$65,316	$45,396	$69,702	$58,307
Column Totals				
Percentage	19%	50%	32%	100%
Income gap	-$4,306	-$2,282	-$5,356	-$2,417
Deductions gap	-$3,440	$0	$4,232	$201
Taxable Income gap	-$866	-$2,282	-$9,588	-$2,618
AGI	$60,026	$39,570	$66,862	$52,038

NOTES:

[a]Income gap equals reported total income less corrected total income.

[b]Deductions gap equals reported deductions (+ adjustments) less corrected deductions (+ adjustments).

[c]Taxable income gap equals reported taxable income less corrected taxable income.

[d]AGI equals total income less adjustments.

TABLE 2C

Cross-Tabulation by Compliance Status
Primarily Wage Income

Total Income	Itemized Deductions + Adjustments			
Over State	**Under State**	**Honest**	**Over State**	**Row Totals**
Percentage	20%	31%	49%	22%
Income gap[a]	$1,056	$426	958	$814
Deductions gap[b]	-$593	$0	$1,172	$455
Taxable Income gap[c]	$1,649	$426	-$215	$360
AGI[d]	$57,945	$29,173	$60,669	$50,436
Honest				
Percentage	10%	61%	29%	64%
Income gap	$0	$0	$0	$0
Deductions gap	-$580	$0	$1,213	$299
Taxable Income gap	$580	$0	-$1,213	-$299
AGI	$52,600	$27,261	$55,557	$38,047
Under State				
Percentage	21%	33%	46%	43%
Income gap	-$2,482	-$979	-$1,855	-$1,704
Deductions gap	-$890	$0	$1,781	$626
Taxable Income gap	-$1,593	-$979	-$3,636	-$2,330
AGI	$58,188	$32,622	$62,746	$51,936
Column Totals				
Percentage	16%	44%	39%	100%
Income gap	-$1,956	-$425	-$970	-$889
Deductions gap	-$2,254	$0	$4,444	$1,380
Taxable Income gap	$298	-$425	-$5,414	-$2,270
AGI	$56,723	$29,141	$60,081	$45,814

NOTES:
[a]Income gap equals reported total income less corrected total income.
[b]Deductions gap equals reported deductions (+ adjustments) less corrected deductions (+ adjustments).
[c]Taxable income gap equals reported taxable income less corrected taxable income.
[d]AGI equals total income less adjustments.

TABLE 3

Tobit Estimates of the Log of the Income and Deductions Gap

Variable	Means (Standard Deviations)	Independent: Log of Income Gap	Independent: Log of Deductions Gap	Simultaneous: Log of Income Gap	Simultaneous: Log of Deductions Gap
Constant	-- (--)	-1.5856 (0.4495)	-8.9662 (0.5893)	-2.0541 (0.4689)	-8.9725 (0.5895)
Log of income	-3.382 (7.812)	-0.4604 (0.0489)	-0.0621 (0.0619)	-0.4163 (0.0505)	-0.0625 --
Log of the income tax price	-0.344 (0.208)	-6.1505 (0.2974)	-- (--)	-6.3303 (0.3018)	(--) (0.6195)
Log of the deductions tax price	-0.259 (0.206)	-- (--)	-3.0136 (0.3648)	-- (--)	-3.0526 (0.3651)
Married	0.693 (0.461)	1.4010 (0.0999)	0.0580 (0.1225)	1.4360 (0.1004)	0.0721 (0.1226)
Family size	2.593 (1.422)	0.1396 (0.0305)	0.0551 (0.0361)	0.1497 (0.0307)	0.0570 (0.0361)
Age	45.81 (16.63)	0.2273 (0.0111)	0.1266 (0.0136)	0.2345 (0.0113)	0.1287 (0.0137)
Age-squared*10^{-3}	2.375 (1.630)	-2.4514 (0.1142)	-1.3110 (0.1364)	-2.5269 (0.1162)	-1.3305 (0.1366)
Wage share	0.669 (1.197)	-1.7704 (0.0559)	— —	-1.7527 (0.0561)	— —
Interest share	0.154 (0.443)	-1.0760 (0.1261)	— —	-1.0514 (0.1261)	— —
PSC	0.314 (0.464)	0.0287 (0.0608)	— —	0.0288 (0.0061)	— —
PSF	0.095 (0.294)	2.2367 (0.1079)	— —	2.1722 (0.1093)	— —
PSE	0.249 (0.433)	2.3113 (0.0774)	— —	2.3397 (0.0778)	— —
PSP	0.183 (0.387)	-0.2282 (0.0887)	— —	-0.1960 (0.0892)	— —
Deductions share	0.228 (0.244)	— —	3.3070 (0.2020)	— —	3.3043 (0.2020)
Itemizer	0.586 (0.444)	— —	4.8268 (0.1328)	— —	4.8206 (0.1328)
LN(deductions gap)	2.093 (7.510)	— —	— —	-0.1340 (0.0376)	— —
LN(income gap)	3.382 (7.812)	— —	— —	— —	-0.0173 (0.0065)
Sigma	--	6.0974 (0.0335)	6.5743 (0.0445)	6.0960 (0.0335)	6.5734 (0.0445)
NOBS	-- 42,811	42,811	42,811	42,811	42,811

NOTE: Standard deviations of the estimated coefficients are provided in parentheses.

Table 4

Two-Stage Tobit of the Log of the Income and Deductions Gaps, by Audit Class

Variable	Audit Class 1			Audit Class 2			Audit Class 3		
	Mean	IGAP	DGAP	Mean	IGAP	DGAP	Mean	IGAP	DGAP
Constant	--	-7.431 (0.905)	-7.905 (1.145)	--	-4.644 (1.122)	-4.427 (1.022)	--	-1.179 (0.708)	-17.078 (1.515)
Log of income	9.530 (0.962)	0.243 (0.107)	-0.401 (0.133)	11.306 (0.696)	0.161 (0.090)	-0.026 (0.079)	10.326 (1.270)	0.437 (0.069)	-0.009 (0.146)
Log of the last dollar income tax price	-0.198 (0.201)	-3.177 (0.817)	--	-0.541 (0.240)	-2.520 (0.159)	--	-0.392 (0.310)	-1.988 (0.409)	--
Log of the last dollar deductions tax price	-0.128 (0.101)	--	-13.027 (1.285)	-0.514 (0.140)	--	0.222 (0.064)	-0.239 (0.210)	--	1.522 (0.846)
Wage-share	0.733 (0.446)	-0.775 (0.196)	--	0.842 (0.850)	0.025 (0.074)	--	0.311 (2.074)	-0.475 (0.068)	--
Interest-share	0.179 (0.528)	-1.309 (0.272)	--	0.138 (0.321)	-0.137 (0.221)	--	0.136 (0.441)	-0.617 (0.121)	--
PSC	0.103 (0.144)	4.268 (0.183)	--	0.230 (0.421)	2.879 (0.127)	--	0.778 (0.416)	0.719 (0.185)	--
PSF	0.021 (0.144)	3.960 (0.346)	--	0.045 (0.207)	2.370 (0.127)	--	0.290 (0.454)	-1.025 (0.173)	--
PSE	0.109 (0.311)	3.968 (0.178)	--	0.383 (0.486)	3.010 (0.115)	--	0.284 (0.451)	0.063 (0.101)	--
PSP	0.051 (0.221)	0.349 (0.248)	--	0.341 (0.474)	-0.050 (0.126)	--	0.170 (0.376)	-0.366 (0.122)	--
Deductions share	0.128 (0.221)	--	8.437 (0.415)	0.354 (0.206)	--	-0.042 (0.283)	0.207 (0.247)	--	0.856 (0.436)
Itemizer	0.286 (0.452)	--	3.090 (0.225)	0.936 (0.245)	--	5.024 (0.274)	0.567 (0.496)	--	6.984 (0.296)
LN(income gap)	1.885 (2.879)	--	0.102 (0.072)	3.146 (3.556)	--	-0.226 (0.063)	6.363 (3.610)	--	1.08 (0.164)
LN(deductions gap)	1.455 (2.701)	0.162 (0.065)	--	3.144 (3.351)	-0.366 (0.113)	--	1.793 (2.923)	-0.422 (0.061)	--
Sigma	--	6.088 (0.066)	7.341 (0.097)	--	6.171 (0.058)	5.838 (0.054)	--	4.300 (0.036)	7.04 (0.106)
Nobs	17,098	17,098	17,098	15,248	15,248	15,248	10,465	10,465	10,465

APPENDIX

We assume that individuals attempt to maximize EU as given by the following equation:

$$EU = (1-P_1)[(1-P_2)U(Z_1) + P_2U(Z_2)] + P_1[(1-P_2)U(Z_3) + P_2U(Z_4)], \quad (1)$$

where $Z_1 = Y - T + E_1 + E_2$; $Z_2 = Y - T + E - \theta_2 E_2$; $Z_3 = Y - T - \theta_1 E_1 + E_2$; and $Z_4 = Y - T - \theta_1 E_1 - \theta_2 E_2$, and that an interior solution $(E_1 > 0$ and $E_2 > 0)$ exists.

Further, we assume the detection probabilities are fixed and independent, or

$$\frac{\partial P_1}{\partial E_1} = \frac{\partial P_1}{\partial E_2} = \frac{\partial P_2}{\partial E_1} = \frac{\partial P_2}{\partial E_2} = 0.$$

Accordingly, the first-order conditions for an interior maximum of (1) are as follows:

$$\frac{\partial EU}{\partial E_1} = (1-P_1)[(1-P_2)U'(Z_1) + P_2U'(Z_2)] - P_1[(1-P_2)\theta_1 U'(Z_3) + P_2\theta_1 U'(Z_4)] = 0 \quad (2)$$

$$\frac{\partial EU}{\partial E_2} = (1-P_1)[(1-P_2)U'(Z_1) - P_2\theta_2 U'(Z_2)] + P_1[1-P_2)U'(Z_3) - P_2\theta_2 U'(Z_4)] = 0 \quad (3)$$

The second-order conditions of a local maximum are given as follows:

$$\frac{\partial^2 EU}{\partial E_1^2} = (1-P_1)[(1-P_2)U''(Z_1) + P_2U''(Z_2)] \quad (4)$$

$$+ P_1[(1-P_2)\theta_1^2 U''(Z_3) + P_2\theta_1^2 U''(Z_4)] < 0$$

$$\frac{\partial^2 EU}{\partial E_2^2} = (1-P_1)[(1-P_2)U''(Z_1) + P_2\theta_2^2 U''(Z_2)] \quad (5)$$

$$+ P_1[(1-P_2)U''(Z_3) + P_2\theta_2^2 U''(Z_4)] < 0$$

$$\frac{\partial^2 EU}{\partial E_1 \partial E_2} = (1-P_1)[(1-P_2)U''(Z_1) - P_2\theta_2 U''(Z_2)] \quad (6)$$

$$- P_1[(1-P_2)\theta_1 U''(Z_3) - P_2\theta_1\theta_2 U''(Z_4)] \lesseqgtr 0$$

We assume that the second-order conditions are satisfied by the concavity of the utility function.

Proposition 1(a): Assuming risk-aversion $(U''<0)$ *and fixed and independent detection probabilities, an increase in the detection probability of a given mode has an ambiguous effect on evasion in both modes.*

By totally differentiating the first-order conditions (2) and (3) with respect to E_1, E_2, and P_1 we obtain the following system of equations:

$$\frac{\partial^2 EU}{\partial E_1^2} dE_1 + \frac{\partial^2 EU}{\partial E_1 \partial E_2} dE_2 = AdP_1 \tag{7}$$

$$\frac{\partial^2 EU}{\partial E_1 \partial E_2} dE_1 + \frac{\partial^2 EU}{\partial E_2^2} dE_2 = BdP_1 \tag{8}$$

Where $A = -(1-P_2)[U'(Z_1)+\theta_1 U'(Z_3)] - P_2[U'(Z_2)+\theta_1 U'(Z_4)] < 0$ and

$$B = (1-P_2)[U'(Z_3)-U'(Z_1)] + P_2\theta_2[U'(Z_2)-U'(Z_4)] \underset{>}{\overset{<}{-}} 0$$

By letting $M = \left[\frac{\partial^2 EU}{\partial E_1^2}\right]\left[\frac{\partial^2 EU}{\partial E_2^2}\right] - \left[\frac{\partial^2 EU}{\partial E_1 \partial E_2}\right]^2$ and noting that $M > 0$ by the

second order conditions of a local maximum, (7) and (8) can be solved, yielding:

$$\frac{dE_1}{dP_1} = \frac{A\frac{\partial^2 EU}{\partial E_2^2} - B\frac{\partial^2 EU}{\partial E_1 \partial E_2}}{M} = \frac{[(-)(-)] - [(?)(?)]}{(+)} \underset{>}{\overset{<}{-}} 0 \tag{9}$$

$$\frac{dE_2}{dP_1} = \frac{B\frac{\partial^2 EU}{\partial E_1^2} - A\frac{\partial^2 EU}{\partial E_1 \partial E_2}}{M} = \frac{[(?)(-)] - [(-)(?)]}{(+)} \underset{>}{\overset{<}{-}} 0 \tag{10}$$

Similar results can be obtained for P_2. Thus, an increase in the detection probability in a given mode has an ambiguous effect on evasion in the targeted mode and increases evasion in the other mode.

Proposition 2(a): Assuming risk-aversion and fixed and independent probabilities of detection, an increase in the penalty of a given mode has an ambiguous effect on evasion in both modes.

By totally differentiating the first-order conditions (2) and (3) by E_1, E_2, and θ_1, we obtain the following system of equations:

$$\frac{\partial^2 EU}{\partial E_1^2} dE_1 + \frac{\partial^2 EU}{\partial E_1 \partial E_2} dE_2 = C \cdot d\theta_1 \tag{11}$$

$$\frac{\partial^2 EU}{\partial E_1 \partial E_2} dE_1 + \frac{\partial^2 EU}{\partial E_2^2} dE_2 = D \cdot d\theta_1 \tag{12}$$

where

$$C = P_1[-(1-P_2)U'(Z_3) - P_2U'(Z_4) + E_1\theta_1[(1-P_2)U''(Z_3) + P_2U''(Z_4)] < 0 \text{ and}$$

$$D = P_1[-(1-P_2)E_1U''(Z_3) + P_2E_1\theta_2U''(Z_4)] \lesseqgtr 0$$

As before, $M = \left[\frac{\partial^2 EU}{\partial E_1^2}\right]\left[\frac{\partial^2 EU}{\partial E_2^2}\right] - \left[\frac{\partial^2 EU}{\partial E_1 \partial E_2}\right]^2$ and $M > 0$ by the second-order conditions of a concave function (11) and (12) can now be solved, yielding

$$\frac{dE_1}{d\theta_1} = \frac{C\frac{\partial^2 EU}{\partial E_2^2} - D\frac{\partial^2 EU}{\partial E_1 \partial E_2}}{M} = \frac{(-)-(?)}{(+)} \lesseqgtr 0 \tag{13}$$

$$\frac{dE_2}{d\theta_1} = \frac{D\frac{\partial^2 EU}{\partial E_1^2} - C\frac{\partial^2 EU}{\partial E_1 \partial E_2}}{M} = \frac{(?)-(-)}{(+)} \lesseqgtr 0 \tag{14}$$

Thus, an increase in a detection penalty in one mode has an ambiguous effect on evasion in both modes.

Proposition 1(b): Assuming risk-neutrality (U' = constant and U" = 0) and fixed and independent probabilities of detection, an increase in the detection probability of a given mode has no effect on evasion in either mode.

Note that U"(∗) = 0; thus, (9) and (10) become

$$\frac{dE_1}{dP_1} = 0 \tag{9'}$$

$$\frac{dE_2}{dP_1} = 0 \tag{10'}$$

In other words, an increase in the detection probability of a given mode has no effect on evasion in either mode. Similar results can be obtained for P_2.

Proposition 2(b): Assuming risk-neutrality (U' = constant and U" = 0) and fixed and independent probabilities of detection, an increase in the penalty of a given mode has no effect on evasion in either mode.

Note U"(∗) = 0; thus, (13) and (14) become

$$\frac{dE_1}{d\theta_1} = 0 \tag{13'}$$

$$\frac{dE_2}{d\theta_1} = 0 \tag{14'}$$

In other words, an increase in the penalty of a given mode has no effect on evasion in either mode. Similar results can be obtained for 2_2.