6-1-1990

Tax Rates and Tax Evasion: Evidence from California Amnesty Data

Steven E. Crane
Marquette University, steven.crane@marquette.edu

Farrokh Nourzad
Marquette University, farrokh.nourzad@marquette.edu

Published version. *National Tax Journal*, Vol. 43, No. 2 (June 1990): 189-199. Permalink.

TAX RATES AND TAX EVASION: EVIDENCE FROM CALIFORNIA AMNESTY DATA**

STEVEN E. CRANE* AND FARROKH NOURZAD*

ABSTRACT

This paper examines the effect of marginal tax rates on income tax evasion using data from the California Tax Amnesty Program. After correcting for the selectivity bias, we find that evaders respond to higher tax rates by increasing their evasion activity. We also find that individuals with higher levels of income tend to evade more. Further, the absolute and relative sizes of both of these effects depend upon the scope of the evasion measure used. Finally, evasion is generally inelastic with respect to changes in both marginal tax rates and income, with the former elasticities tending to be larger.

I. Introduction

TAX rates have been widely recognized as a primary determinant of income tax evasion. In fact, one argument in favor of cutting marginal tax rates has been that, by inducing greater income reporting, lower rates will broaden the tax base. While intuitively appealing, this claim has not been substantiated by traditional microtheoretic analyses (e.g., Allingham and Sandmo, 1972), which have generally found that consequences of a tax rate change to be, *a priori*, indeterminate. Recent efforts to analyze this issue in a game theoretic context have even resulted in a negative relationship between tax rates and evasion (e.g., Graetz, Reinganum, and Wilde, 1986). Empirical analyses have also been unable to resolve this issue. Some studies ignore the matter altogether by omitting tax rates (e.g., Witte and Woodbury, 1985). Other studies that do include a marginal tax rate variable obtain mixed results, ranging from no effect (e.g., Slemrod, 1985) to a positive effect (e.g., Clotfelter, 1983). Thus further research using alternative sources of data is warranted.

*Marquette University, Milwaukee, Wisconsin 53233.

In this paper we examine the impact of marginal tax rates on income tax evasion using data from the California Income Tax Amnesty Program. Amnesty data represent a new source of micro data which allows construction of direct measures of tax evasion. However, the selectivity bias inherent in such data requires special econometric treatment. This involves using a maximum likelihood technique that incorporates not only the variables influencing the evasion decision, but also those influencing the subsequent decision to participate in the amnesty program. Our findings indicate that, after controlling for the effects of other relevant variables, there is a statistically significant positive relation from marginal tax rates to alternative measures of evasion.

The remainder of this paper is organized as follows. In the next section some general background regarding existing theoretical and empirical work on the tax rate effect is provided. This is followed by Section III which contains a discussion of the features of the sample data employed in this study. In Section IV, we present a description of the variables used in our empirical model. The estimation procedure is outlined in Section V, followed by a discussion of our findings in Section VI. The final section provides a summary of this work and offers some suggestions for further research.

II. Background

Since the classic work by Allingham and Sandmo (1972), the standard approach to analyzing the individual's evasion decision has been to use a portfolio-choice framework in which the optimal level of evasion is obtained from maximizing expected utility of income after taxes and penalties. Using this approach, four factors have been commonly found to affect the decision to evade. These are the individual's true income, the tax rate, the probability that the evader is detected, and the penalty rate to which detected evaders are subjected. In most cases, a positive relationship between the level of evasion and the individual's true income, and negative relations with both of the compliance policy tools are obtained. With respect to the tax rate, however, most models have been unable to determine an unambiguous relation.[1]

This ambiguity is due to the fact that a change in the tax rate exerts two opposing effects on the taxpayer. On the one hand, an increase in the tax rate induces greater evasion since it increases the marginal return to successful evasion (the substitution effect). On the other hand, by reducing disposable income, a higher tax rate generates an additional effect (the income effect) which may lead to more or less evasion depending on the individual's attitude towards risk. To the extent that an individual is less willing to take risk as his/her after-tax income declines, he/she will be less inclined to evade taxes when the tax rate increases. Therefore, unless risk aversion increases with income, or the substitution effect is strong enough to dominate the income effect, one obtains the counter-intuitive result that higher tax rates lead to reduced evasion, or that the effect is indeterminate.[2]

More recently, income tax evasion has been examined within a game-theoretic framework which explicitly recognizes strategic aspects of the interaction between the taxpayer and the tax authority (e.g., Graetz, Reinganum, and Wilde, 1986; Reinganum and Wilde, 1986, 1988). In this context, a tax rate change generates an additional effect through its impact on the marginal return to auditing. It has been shown that, under some simplifying assumptions and for certain audit classes, this effect dominates the conventional tax rate effect leading to a negative overall impact (Graetz, Reinganum, and Wilde, 1986). This result holds independently of the taxpayer's attitude towards risk.

It is interesting to note that the one prediction that has not been established theoretically is the one that casual observers expect, that higher taxes lead to greater evasion. Given this lack of consensus regarding the theoretical and intuitive expectations about the net tax rate effect, one is inclined to turn to the empirical evasion literature for evidence.

Any attempt to conduct an empirical investigation of tax evasion must first overcome severe measurement difficulties as evasion is inherently unobservable. A variety of rather innovative approaches has been employed to deal with this problem. Some researchers (e.g., Friedland, Maital, and Rutenberg, 1978; Geeroms and Wilmots, 1985; Spicer and Becker, 1980) have designed experiments or have conducted surveys in order to generate relevant data. Others (e.g., Crane and Nourzad, 1986; Tanzi, 1983) have approached the problem from a macroeconomic perspective. An attempt has even been made at developing an evasion index from the distribution of tax returns across tax brackets (Slemrod, 1985). Only a few authors (e.g., Clotfelter, 1983; Dubin and Wilde, 1988; Klepper and Nagin, 1989; Witte and Woodbury, 1985) have been able to develop direct measures that are representative of evasion behavior under actual tax systems. Of these, only Clotfelter has been able to examine the issue at the individual level.

Not all empirical studies of tax evasion have addressed the tax rate-evasion issue (e.g., Spicer annd Lundstedt, 1976; Witte and Woodbury, 1985). Those that have considered tax rates have obtained mixed results, ranging from no effect (e.g., Geeroms and Wilmots, 1985; Klepper and Nagin, 1989; Slemrod, 1985) to a significant positive effect (e.g., Friedland, Maital, and Rutenberg, 1978; Tanzi, 1983; and most notably, Clotfelter, 1983). Note that the one prediction that has not been supported empirically is that higher taxes lead to lower evasion. Clearly, more research, perhaps using data from alternative sources, is needed. We believe that data from state income tax amnesty programs provide a new and thus far unexploited opportunity to search for new evidence on this issue.

In what follows we analyze evasion of state income taxes in California using data from that state's tax amnesty program. In doing so, we assume that the decision to evade state income taxes is independent of the decision to evade federal taxes. To date, no one has examined the possible complications that might arise from the interaction between these two decisions in a framework which incorporates multiple tax and enforcement systems. Consequently, it is not clear whether we should view federal and state income tax evasion as substitute or complementary activities. Furthermore, addressing this issue empirically would require matching information from the individuals' federal returns. Unfortunately, we were unable to gain access to these returns.

III. The California State Income Tax Amnesty Program

Following a number of other states, California introduced a tax amnesty program which ran from December 10, 1984 to March 15, 1985.[3] The primary purpose of this program as stated by the California Tax Franchise Board (CTFB) (California Amnesty Program, 1986, p. 1) was to

> provide a number of far-reaching enforcement tools that significantly improved the state's ability to identify and collect tax obligations from individuals previously beyond the reach of traditional enforcement programs.

Under this program, unpaid penalties and criminal prosecution were waived for qualified individuals. However, accrued taxes and interest charges were not forgiven. Those eligible for amnesty included individuals who, for 1983 or an earlier tax year, had failed to file personal income tax returns, had filed inaccurate returns, or were delinquent in paying their tax liabilities. Amnesty was not available to those already under criminal investigation.

There were over 145,000 returns filed by about 85,000 individuals under this program, and roughly $154 million in gross revenue was produced. According to CTFB estimates this is $34.5 million more than what would have been collected through the traditional enforcement programs. Thus, in contrast to the experience of many other states, California was successful in generating a significant amount of net revenue.

As noted above, revenue generation was not the sole objective of the California Amnesty Program, as it "was also expected to provide valuable information on characteristics of tax evaders and the methods used to evade taxes," (California Amnesty Program, 1986, p. 5). With this in mind, the CTFB identified amnesty returns filed by individuals who were either not already known to the CTFB, or would not have been detected through normal enforcement procedures. The CTFB then drew a random sample from the amnesty returns submitted by individuals who had not originally filed in the year for which they claimed amnesty. Another sample was taken from the more than 7,000 returns filed by those who amended their original returns under the program. For each of the 186 individuals in the latter sample, the CTFB combined the information on the amended return with relevant data taken from that taxpayer's original return. To ascertain the characteristics of the individuals in these samples, the CTFB commissioned Sheffrin (1985) to conduct a descriptive study.

Once this descriptive study was completed, the CTFB furnished us with these data. Because our objective is to conduct econometric analysis we focus on the sample of individuals who filed amended returns. This is required if we are to be consistent with standard theoretical evasion models which derive comparative static results for the interior solution of partial income under-reporting, and to avoid corner solutions of complete honesty and dishonesty.

Prior to carrying out our econometric analysis, we examined the data for internal consistency. This involved recalculating the tax bill on both the original and amended returns of each of these 186 individuals. In the process we discovered a number of problem observations. These were primarily missing data, obvious taxpayer or data entry errors, inability to duplicate tax calculations, and in a few cases no change or a drop in total tax liability. After removing the observations with these problems, the sample size was reduced to 123 observations. We have no reason to suspect these omissions bias the sample.

Of much greater concern is the probable bias due to the self-selected nature of the sample. Clearly, those evaders who voluntarily chose to participate in the amnesty program may not be representative of the population of California state income tax evaders as a whole. Fortunately, while complicated, it is possible to deal with this type of self-selection bias econometrically. However, we postpone our discussion of the appropriate estimation procedure until after we have described our empirical model and the data to which it is applied.

IV. Model Specification and Quantification

As mentioned in Section II, theoretical tax evasion models generally express evasion as a function of marginal tax rate, true income, penalty rate, and probability of detection. Of these, the most difficult to quantify has usually been the dependent variable measuring evasion. However, our amnesty dataset greatly simplifies this task.

A. Measuring Evasion

Because our sample includes information taken from both the original returns and the amended returns filed under amnesty, construction of an evasion measure is straightforward. If we assume that the amended returns represent the "truth," we can simply compare the figures on these returns with their counterparts on the original returns. This is a plausible assumption since it seems unlikely that one who has voluntarily admitted to evading on a particular tax return would turn around and file a false amended return. This is especially true in the case of the California Amnesty Program, given that it was publicly announced that the amended returns themselves may be audited, that amnesty filers would be flagged for future reference, and that any information received through the program would be available to the IRS.

Of course, which figures are to be compared depends upon how evasion is defined. Evasion can take place in a number of ways. An individual may choose to underreport his/her true income. He/she may also overstate adjustments in moving from Total Income to Adjusted Gross Income (AGI), or claim excessive deductions from AGI when calculating Taxable Income. Finally, once the tax liability associated with a given Taxable Income is determined, one can claim excessive credits against this tax liability when calculating his/her taxes owed.[4] An individual may also choose to evade using any combination of these methods.

With our sample data we are able to construct measures for different combinations of these forms of evasion. One measure, which reflects all of the above methods of evasion, is the amount of taxes evaded, calculated by subtracting taxes owed on the original return from taxes owed on the amended return. An alternative measure can be constructed by subtracting Taxable Income on the original return from that on the amended return. This captures understatement of true income as well as overstatement of adjustments and deductions. We can also calculate a measure based on Adjusted Gross Income by subtracting the AGI figure reported on the original return from that on the amended return. This measure ignores any overstatement of deductions in moving from AGI to Taxable Income. Finally, we can measure pure underreporting of income by subtracting Total Income reported on the original return from Total Income on the amended return.

These measures have a number of advantages. First and foremost, they are direct measures of evasion in that they are based on actual individual tax returns. To date, only Clotfelter's (1983) study of the data from the 1969 Tax Compliance Measurement Program (TCMP) has utilized such a direct measure at the individual level.[5] Second, unlike the TCMP figures, the amnesty-based measures do not depend on the auditor's ability to detect evasion.[6] Offsetting these advantages is the previously mentioned self-selection problem, which is discussed in Section V.

B. *Measuring the Determinants of Evasion*

Given our assumption that the taxpayer is truthful when filing under amnesty, we use the information on the amended return for some of our independent variables. In particular, we use the total income figure on the amended return as our measure of true income. Similarly, the true marginal tax rate (ranging from one to eleven percent) is calculated by applying the appropriate tax table to the taxable income reported on the amended return.

As with most empirical analyses, our data place some restrictions on the extent to which we are able to directly control for other relevant factors. The fact that the sample is primarily cross-sectional, coupled with the uniformity of California's penalty rate across individuals and over the three-year sample period, means that no penalty rate can be included in the model. On the other hand, subjective assessment of the detection probability certainly varies across individuals, and it is at least conceptually possible to have a different value for each individual.

In practice, however, reliable measures of this subjective probability are not typically available. A common alternative has been to use some measure of the objective audit probability as a proxy. With this in mind, we asked the Compliance Development Liaison of the CTFB to provide us with an estimate of the probability that each of the *original* returns would have been audited under the audit selection rules in force at the time of filing. Understandably, the CTFB was not willing to disclose such sensitive information in detail. However, the Liaison did classify each original return as having had a high, medium or low probability of being audited under the pre-amnesty regime. Therefore, we control for the detection probability using two dummy variables to distinguish the CTFB's medium and high classifications from the low. We recognize that these are less than ideal controls for the detection probability, but, after considerable effort, we are convinced they are the best measures available to us.[7]

In addition to the variables identified by theory, previous empirical evidence suggests that one should also control for such taxpayer characteristics as marital status and occupation. In all cases, these should reflect the conditions that existed at the time evasion took place. Therefore, we construct dummy variables for these characteristics using information taken from the original return.[8] Of course, it would be desirable to include a wider range of socio-demographic characteristics such as taxpayers' age, race, and the like. However, data limitations preclude us from doing so.

To summarize, our empirical model of income tax evasion alternatively uses Evaded Taxes (TAXGAP), Taxable Income Gap (TIGAP), and Adjusted Gross Income Gap (AGIGAP) as the regressand.[9] All three regression equations use as primary regressors true income (Y) and marginal tax rate (MTR). Based on the standard evasion theory we expect the income variable to have a positive sign. On the other hand, given our earlier discussion of the tax rate effect, we have no sign expectation for the tax rate variable. The regression equations also include dummy control variables for probability of detection (MEDIUM, HIGH), occupation (MGR/PROF, SALES, CLERICAL), and marital status (MS). We expect the two probability variables to have negative signs since the omitted category represents individuals with low probability of being detected. We have no clear sign expectations for the other dummy variables.

V. Estimation Procedure

Our objective is to estimate a regression equation of the following form

$$y_i = X_i\beta + u_i, \quad i = 1,2, \ldots, n \tag{1}$$

where y_i is a measure of evasion, X_i is a vector of the determinants of evasion, β is a vector of unknown parameters, and u_i is a random error term with mean zero and variance σ^2. Because our sample is self selected, estimating (1) using ordinary least squares (OLS) would result in biased estimates and therefore an alternative approach must be employed.[10]

Correcting the selectivity bias in amnesty data is complicated by the fact that the sample is truncated; information is available on the evasion decision of those who participated in the amnesty program, but there is no information whatsoever on nonparticipants. In this case, the proper estimation procedure requires knowledge of factors that influenced the decision of the evaders in our sample to participate in the amnesty program. If such factors can be identified, one can obtain unbiased maximum likelihood (ML) estimates of the parameters of (1) using the following likelihood function (Maddala, 1983, pp. 266–67),

$$\prod_i \left[\frac{\Phi\{[Z_i\delta - (\rho/\sigma)(y_i - X_i\beta)]/(1-\rho^2)^{1/2}\}}{\Phi(Z_i\delta)}\right](2\pi\sigma^2)^{-1/2}\exp\left[-\frac{1}{2\sigma^2}(y_i - X_i\beta)^2\right] \tag{2}$$

where Z_i is a vector of factors influencing the participation decision, δ is a vector of unknown parameters, $\Phi(\cdot)$ is the distribution function of the standard normal, $\int$ is the correlation coefficient between u_i and the error term of the participation function, and all other notations are as defined previously.[11]

The term in the large bracket is the ratio of the conditional probability of participation in the amnesty program, given $(y_i - X_i\beta)$, to the unconditional probability of participation. The term outside of this bracket is the density function of $(y_i - X_i\beta)$. Thus the bias-correction procedure involves scaling the density function of $(y_i - X_i\beta)$ using the ratio of the two probabilities as weights. This procedure yields unbiased estimates for the parameters of the evasion model (the βs), even though the estimates of the parameters of the participation function (the δs) are unreliable. However, given that we are interested in the former set of estimates, the unreliability of the estimates of δ is no cause for concern.

In order to apply this estimation procedure we need to specify the components of the vector Z_i. In a recent article in this journal, Fisher, Goddeeris, and Young (1989) suggest that the decision to participate in amnesty programs is influenced by the perceived increase in the post-amnesty penalty rate and probability of detection.[12] Here, as in our evasion model, we focus on the latter influence since we are unable to control for the effect of changes in the penalty rate given that our sample is cross-sectional, and the higher post-amnesty penalty rate applied uniformly to all individuals.

The perceived increase in the probability of detection is likely to depend upon what the individual can learn about the program. A good source of information is the amnesty legislation itself. The California Amnesty Bill stated explicitly that, among other things, returns with self-employment income (Schedule C) and capital gains (Schedule D) would be targeted for intensified enforcement efforts after the amnesty period expired. Thus regardless of the form of evasion, an individual whose tax return included these schedules should have expected to face increased scrutiny post amnesty.[13] Hence it is reasonable to assume that evaders with incomes from these sources were more likely to have participated in the program. To capture this effect, we create dummy variables to reflect the presence of these two schedules in the individual's original return.

Other factors not directly related to the amnesty program could also have contributed to changes in the perceived probability of detection, thereby inducing participation. A prime example would be a notice from the IRS of an impending audit of the federal return. It seems likely that those evaders of California income taxes who had recently come under investigation by the IRS would have expected their probability of detection at the state level to have risen. In order to control for this effect, we construct a dummy variable indicating a positive response to an explicit question on the amended return regarding whether the participant was under IRS audit at the time of filing for state amnesty.

To summarize, the participation decision is incorporated into the likelihood function (2) through the variables SCH-C, SCH-D, and IRS-AUDIT. We recognize that this participation function is somewhat *ad hoc* and that we have probably oversimplified the complex participation decision. However, to date there has been no formal theoretical modeling of amnesty participation, and we are greatly constrained by data availability.

VI. Estimation Results

The maximum likelihood estimation results for each of our three measures of evasion are presented in Table 1.[14] The top of each column of this table contains the mean value of the dependent variable, the log of the likelihood function at the optimum, the calculated chi-squared statistic, and the estimated correlation coefficient between the error terms of the evasion and participation functions. These are followed by the estimated parameters of both the evasion and participation functions (i.e., the βs and δs in Equation 2 above).[15]

We begin our discussion of the results by noting that, based on the chi-squared statistics, each estimated equation is statistically significant. Next we consider the individual parameter estimates associated with the qualitative variables of the evasion function. The two dummy probability variables representing the CTFB's audit groupings have the expected negative signs, which would suggest that evaders with medium or high audit probabilities tend to evade less than those with low probabilities. Further, as would be expected, the coefficient of HIGH is larger in absolute value than that of MEDIUM. However, since these estimates are never statistically significant, not much should be made of these results.

The marital status variable is positive in all three equations and approaches statistical significance at conventional levels suggesting that, other things equal, married taxpayers tend to evade more. This finding is consistent with some previous empirical work on the evasion problem (e.g., Friedland, Maital, and Rutenberg, 1978). Finally, of the occupational classifications, only the managerial/professional category has a t-ratio greater than unity in all three equations. It appears that in our sample either evasion does not vary across occupations, or more detailed occupational classifications are needed to capture whatever effect there may be.

Turning to the quantitative variables, we find that true income has the expected positive sign and is statistically significant in all equations, a finding consistent with all previous empirical evasion studies. More important for our purposes, however, is the fact that the marginal tax rate variable is positive and statistically significant at reasonable levels of confidence in all three equations. This is in line with Clotfelter's (1983) finding, as well as with the popular contention that higher tax rates lead to increased evasion. It is also consistent with the usual microtheoretic prediction that the substitution effect of a change in relative prices typically outweighs the income effect.[16]

Despite consistent results with respect to the sign and significance of income and tax rate across all equations, there is a clear difference in the magnitudes of these coefficients in Equation 1 compared to the other two equations. In particular, both coefficients are markedly smaller in Equation 1, reflecting the much smaller mean value of TAXGAP.[17] This highlights the conceptual difference between TAXGAP, which reflects taxes evaded, and the other measures of evasion which represent understatement of various types of

TABLE 1
MAXIMUM-LIKELIHOOD ESTIMATION RESULTS
(Absolute Value of Asymptotic t-Ratios in Parentheses)

	EQUATION 1 TAXGAP	EQUATION 2 TIGAP	EQUATION 3 AGIGAP
MEAN	342.98	4265.60	4009.50
LLF	-924.15	-1217.26	-1216.57
CHI-SQR	38.55	21.32	23.70
CORR. COEF.	0.04	-0.09	0.02
TAX EVASION VARIABLES			
INTERCEPT	-322.78	213.02	8.31
	(2.00)	(0.12)	(0.007)
INCOME	0.002	0.018	0.018
	(4.25)	(3.46)	(3.56)
MTR	62.77	331.13	315.17
	(3.79)	(1.85)	(2.42)
MEDIUM	-33.48	-402.20	-666.42
	(0.37)	(0.41)	(0.68)
HIGH	-119.49	-618.60	-2222.14
	(0.38)	(0.18)	(0.64)
MS	147.78	1635.57	1901.07
	(1.56)	(1.59)	(1.96)
MGR/PROF	-124.30	-1501.10	-1253.66
	(1.35)	(1.51)	(1.27)
SALES	-26.52	-776.02	-2363.89
	(0.10)	(0.27)	(0.83)
CLERICAL	41.14	47.82	-761.02
	(0.22)	(0.02)	(0.38)
AMNESTY PARTICIPATION VARIABLES			
INTERCEPT	4.47	5.40	4.60
	(0.032)	(0.005)	(0.003)
IRS-AUDIT	-0.004	0.05	0.24
	(0.000)	(0.000)	(0.000)
SCH-C	0.24	0.14	-0.16
	(0.005)	(0.000)	(0.000)
SCH-D	0.41	-0.65	-0.23
	(0.003)	(0.000)	(0.000)

income. In light of these differences, a comparison of elasticities is more meaningful. This also allows us to evaluate the relative effects of changes in true income and marginal tax rate on different measures of evasion.

The estimates from Table 1 are converted into elasticities using mean values and the results are reported in Table 2. Note that Equation 1 remains distinct from the other two, except that now it exhibits the largest relative effects with respect to both true income and marginal tax rate, whereas previously it displayed the smallest absolute effects. Table 2 also reveals that within each equation the tax rate elasticity is considerably larger than the income elasticity. However, with the exception of the tax rate elasticity in Equation 1, the evasion response to these two variables is inelastic. The large tax rate elasticity in Equation 1 may be attributable to the fact that the TAXGAP reflects all types of evasion and thus captures the entire response to tax rate changes, while the other evasion measures only capture a portion of this response.

Before concluding, a few words regarding the estimated parameters of the participation function are in order. By usual standards, these estimates are quite poor. However, it is not clear what is to be made of the sign, significance, or magnitude of these coefficients; it is normally not possible to obtain reliable estimates for the participation parameters, even though their inclusion in the likelihood function corrects the selectivity bias. Thus the poor estimates of the participation parameters need not be a serious cause for concern.

VII. Concluding Remarks

In this paper we have studied the behavior of state income tax evaders who took advantage of the California Tax Amnesty Program. In the process, we have shown how amnesty data can be utilized to construct alternative measures of evasion, and have demonstrated how existing econometric techniques can be used to deal with the inherent self-selection problem. Our findings support the popular contention that evaders respond to higher marginal tax rates by increasing their evasion activity.

The results also confirm the theoretical prediction that individuals with higher levels of income tend to evade more. Further, the absolute and relative sizes of both of these effects depend upon the scope of the evasion measure used. In particular, the absolute effects of income and tax rate changes are larger for the income-based measures of evasion, while the relative effects are larger for the tax-based measure of evasion. Finally, our results suggest that evasion is generally inelastic with respect to changes in both true income and marginal tax rates, but that tax rate elasticities are consistently larger than income elasticities.

Analysis of evasion using amnesty data can be improved in a number of ways. First, more attention should be given to the participation function, including both formal modeling and use of better empirical counterparts for the resulting arguments. Second, amnesty data from other states should be examined to see if the results reported here can be substantiated. Third, the sensitivity of different types of

TABLE 2
ELASTICITIES OF VARIOUS MEASURES OF EVASION WITH RESPECT TO TRUE INCOME AND MARGINAL TAX RATE EVALUATED AT MEANS

	TAXGAP	TIGAP	AGIGAP
Income (Y)	0.29	0.21	0.22
Tax Rate (MTR)	1.50	0.64	0.65

evasion to enforcement-related variables should be examined, preferably, in a model that incorporates a more complete treatment of the endogeneity problem associated with the detection probability. Finally, the possible interaction between state and federal income tax evasion should also be investigated.

ENDNOTES

**We wish to thank James Morandi, Luis Reves, and James Shephard of the California Tax Franchise Board for helping us gain access to the data used in this study. The views expressed are those of the authors and do not necessarily reflect the views of the Tax Franchise Board. We would also like to thank our colleagues at Marquette University and three anonymous referees for helpful comments. Financial support from the Marquette University College of Business Miles Fund is gratefully acknowledged.

[1]Other factors have also been considered in this framework. These include the taxpayer's labor supply decision (e.g., Sandmo, 1981) and the progressivity of the tax system (e.g., Marchon, 1979). The consequence has usually been to make the comparative static results even more ambiguous.

[2]Yitzhaki (1974) showed that if taxes are proportional and fines are levied on evaded taxes rather than evaded income, there would be no substitution effect. As a result, if risk aversion is decreasing with income, the effect on evasion of a change in the tax rate is negative.

[3]For a comparative survey of the general provisions of various states' amnesty programs see Mikesell (1986).

[4]In addition to claiming excessive credits when calculating the tax bill one can understate other taxes such as minimum tax on preference income or taxes on early withdrawals from Individual Retirement Accounts.

[5]Other studies have also used TCMP data but not at the individual level (e.g., Dubin and Wilde, 1988; Klepper and Nagin, 1989; Witte and Woodbury, 1985).

[6]For more on the shortcomings of the TCMP data see Graetz and Wilde (1985).

[7]Our audit classification dummies serve as instrumental variables for the detection probability, which is likely to be endogenous. However, because these probability measures can ultimately be traced back to the information contained in the returns, they too may be endogenous and, therefore, may not be good instruments.

[8]Only broad occupational categories are available. These are: managers and professionals (MGR/PROF), salespersons (SALES), clerical workers (CLERICAL), and laborers (LABOR). LABOR is used for the base category. Marital status is represented by a dummy variable, (MS), identifying married taxpayers.

[9]We will not estimate a model with Total Income Gap as the dependent variable. This would involve additional econometric problems as discussed in note 11 below.

[10]For a survey of the literature on the selectivity bias that arises from different types of self-selected samples, along with remedial procedures see Maddala (1983, Ch. 9). Also see Wainer (1986), especially the contribution by Heckman and Robb, pp. 63–107.

[11]As mentioned in note 9, we do not estimate a model with Total Income Gap as dependent variable. This is because the self-selection correction procedure would be further complicated by the fact that there are many observations in our sample for which this variable is zero.

[12]They also discuss the role of personal guilt in this decision.

[13]The fact that the pre-amnesty probability of being audited might have depended on the presence of these two schedules does not undermine our line of reasoning. What we are arguing is that their presence in one's original return has an additional effect post amnesty.

[14]We also estimated these equations using OLS and obtained results that are qualitatively consistent with those reported in the text. Quantitatively, the parameter estimates for the amount of taxes evaded, TAXGAP, which captures all forms of evasion, were virtually identical to the ML results. Those for the first income-based measure, TIGAP, which ignores overstatement of tax credits, were modestly different. In contrast, the results of the AGIGAP, which reflects only misstatement of income and adjustments, are notably different from the corresponding ML estimates. Evidently, the impact of the selectivity-bias correction procedure used here increases as the scope of the evasion measure narrows.

[15]We acknowledge that applying maximum likelihood to a sample of 123 observations may not generate the most robust results.

[16]Our finding that marginal tax rates are positively correlated with the level of evasion conflicts with the prediction from the game-theoretic models of tax evasion (e.g., Graetz, Reinganum, and Wilde, 1986). This may be due, in part, to our crude treatment of the probability of detection. On the other hand, as these authors have pointed out, the game-theoretic results are perhaps best interpreted as applying across a narrow range of income as within a particular audit class. As a result, their theoretical predictions and our empirical results may not be directly comparable.

[17]The small mean value of TAXGAP should not be taken as trivial. As a point of reference, consider that the average tax liability of the 1983 state income tax return was $769.

REFERENCES

Allingham, Michael G., and Agnar Sandmo, "Income Tax Evasion: A Theoretical Analysis," *Journal of Public Economics,* 1 (Nov. 1972) 323–338.

California Tax Franchise Board, *California Amnesty Program,* (1986).

Clotfelter, Charles T., "Tax Evasion and Tax Rates: An Analysis of Individual Returns," *Review of Economics and Statistics,* 65 (Aug. 1983) 363–373.

Crane, Steven E., and Farrokh Nourzad, "Inflation and Tax Evasion: An Empirical Analysis," *Review of Economics and Statistics,* 68 (May 1986) 217–223.

Dubin, Jeffrey and Louis L. Wilde, "An Empirical Analysis of Federal Income Tax Auditing and Compliance," *National Tax Journal,* 41 (March 1988) 61–74.

Fisher, Ronald C., John H. Goddeeris, James C. Young, "Participation in Tax Amnesties: The Individual Income Tax," *National Tax Journal,* 42 (March 1989) 15–28.

Friedland, N., S. Maital, and A. Rutenberg, "A Simulation Study of Income Tax Evasion," *Journal of Public Economics,* 10 (1978) 107–16.

Geeroms, Hans, and Hendrik Wilmots, "An Empirical Model of Tax Evasion and Tax Avoidance," *Public Finance/Finances Publiques,* 40 (1985) 190–209.

Graetz, Michael J., and Louis L. Wilde, "The Economics of Tax Compliance: Facts and Fantasy," *National Tax Journal,* 38 (September 1985) 355–63.

Graetz, Michael J., Jennifer F. Reinganum, and Louis L. Wilde, "The Tax Compliance Game: Toward an Interactive Theory of Law Enforcement," *Journal of Law, Economics, and Organization,* 39 (Spring 1986) 1–32.

Klepper, Steven, and Daniel Nagin, "The Anatomy of Tax Evasion," *Journal of Law, Economics, and Organization,* 5 (Spring 1989) 1–24.

Maddala, G. S., *Limited-Dependent and Qualitative Variables in Econometrics,* Cambridge University Press, (1983).

Marchon, Maurice N., "Tax Avoidance, Progressivity, and Work Effort," *Public Finance/Finances Publiques,* 34 (1979) 453–59.

Mikesell, John L., "Amnesties for State Tax Evaders: The Nature of and Response to Recent Programs," *National Tax Journal,* 39 (December 1986) 507–25.

Reinganum, Jennifer F. and Louis L. Wilde, "Equilibrium Verification and Reporting Policies in a Model of Tax Compliance," *International Economic Review,* 27 (October 1986) 739–60.

Reinganum, Jennifer F. and Louis L. Wilde, "A Note on Enforcement Uncertainty and Taxpayer Compliance," *Quarterly Journal of Economics,* (November 1988) 793–98.

Sandmo, Agnar, "Income Tax Evasion, Labor Supply, and the Equity-Efficiency Tradeoff," *Journal of Public Economics,* 16 (1981) 265–88.

Sheffrin, Steven M., "An Analysis of Returns Filed Under Amnesty: A Report to the Franchise Tax Board," unpublished manuscript, (Nov. 1985).

Slemrod, Joel, "An Empirical Test for Tax Evasion," *Review of Economics and Statistics,* 67 (May 1985) 232–238.

Spicer, Michael W., and L. A. Becker, "Fiscal Inequity and Tax Evasion: An Experimental Approach," *National Tax Journal,* 33 (June 1980) 171–5.

Spicer, Michael W., S. B. Lundstedt, "Understanding Tax Evasion," *Public Finance/Finances Publiques,* 31 (1976) 295–305.

Tanzi, Vito, "The Underground Economy in the United States: Annual Estimates, 1930–80," International Monetary Fund *Staff Papers,* 30 (June 1983) 283–305.

Wainer, Howard, ed., *Drawing Inferences From Self-Selected Samples,* Springer-Verlag (1986).

Witte, Ann D., and Diane F. Woodbury, "The Effect of Tax Laws and Tax Administration on Tax Compliance: The Case of the U.S. Individual Income Tax," *National Tax Journal,* 38 (Mar. 1985) 1–13.

Yitzhaki, Shlomo, "A Note on Income Tax Evasion: A Theoretical Analysis," *Journal of Public Economics,* 3 (May 1974) 201–202.