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AN EMPIRICAL ANALYSIS OF FEDERAL INCOME TAX AUDITING AND COMPLIANCE

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ABSTRACT

This paper provides empirical evidence on the relationship between compliance with the Federal Income Tax and auditing by the Internal Revenue Service. It combines a cross-section data set related to 1969 individual returns assembled by the IRS with data taken from the Annual Report of the Commissioner of Internal Revenue. We find strong support for an economic approach to tax compliance, but one that incorporates the IRS as a strategic actor. In particular, while audits may have a deterrent effect on noncompliance, we find that they are themselves, in the majority of cases, responsive to the pattern of compliance.

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1. INTRODUCTION

Despite roughly fifteen years of theoretical work devoted to understanding compliance with the tax laws and a recent surge in attention paid to it by tax policymakers and administrators, empirical work on tax compliance is still in its infancy, especially with respect to micro-level studies. Yet, the "facts" of tax compliance are asserted routinely, almost without qualification. For example, commissioners of the IRS report regularly to Congress and the public on the size and growth rate of the so-called "compliance gap," proponents of tax reform nearly always list improved compliance as one of the major benefits of lower marginal tax rates, and even Congress acts at times as though the economics-of-crime model has been demonstrated to be the best representation of the compliance problem (Graetz and Wilde, 1985).

All of this is highly problematic. The basic economics-of-crime approach takes the audit policies of the IRS as fixed and exogenous and models the taxpayer's compliance decision as a simple portfolio problem—reported income is the safe asset and unreported income is the risky asset. Generally this model predicts that either increases in the probability of apprehension and conviction or the penalty for underreporting will increase compliance, but the empirical evidence on these effects is both weak and scanty (see Sections 2 and 3 below). Furthermore, a strong case can be made that IRS activity ought not be taken as given, but instead be made endogenous (Graetz, Reinganum, and Wilde, 1986).

The purpose of this paper is to provide some empirical evidence on the relationship between audits and compliance. Our analysis uses in part a cross-section data set related to 1969 individual Federal Income Tax returns which was assembled by the IRS in the seventies. This data set includes an estimated compliance variable, a number of agency variables such as audit rates, and other demographic and socio-economic variables for each of seven audit classes, aggregated to the three digit zip code level. Audit classes are defined by income level (low, medium, or high) and by type of return (1040 only, Schedule C or F present, Schedule C and F not present).[1] We also use data taken from the Annual Report of the Commissioner of Internal Revenue.

Generally speaking, we find strong support for an economic approach to tax compliance, but one that incorporates the IRS as a strategic participant in the revenue collection process. In particular, for low income classes, increases in the audit rate tend to be associated with increases in percentage compliance, but for middle and upper income classes there is a nonpositive relationship between audits and compliance. In the latter cases, though, the audit rate itself is endogenous. Thus, a deterrent effect of audits may be present in middle and upper income classes, but, in equilibrium,

the "yield effect" dominates the deterrent effect.

Section 2 of this paper summarizes the traditional decision-theoretic model of tax compliance and recent game-theoretic extensions of it which incorporate the IRS into an interactive theory of auditing and compliance. Section 3 discusses existing micro-level studies of tax compliance. Section 4 then describes the data set used in this paper, Section 5 the estimation itself, and Section 6 the results.

2. THE ECONOMIC THEORY OF TAX COMPLIANCE

The contemporary revival of the economic analysis of crime began in 1968 with Becker's classic article "Crime and Punishment: An Economic Approach." While Becker mentioned tax evasion as an area of application for his general model, Allingham and Sandmo (1972) and Srinivasan (1973) provided the analysis. Generally, this approach treats noncompliance as a rational individual decision based upon probabilities of detection and conviction and levels of punishment. In Allingham and Sandmo's model, the taxpayer's actual income is exogenously given and known by the taxpayer but not the IRS. A constant proportional tax is applied to reported income, the amount of which is chosen by the taxpayer. With some exogenous and constant probability, the taxpayer is "audited." If he or she is discovered to be underreporting income, a penalty proportional to the amount of undeclared income, at a rate higher than the proportional tax rate, must be paid. The taxpayer chooses a level of reported income so as to maximize his or her expected utility of net wealth.

Even this simple model produces ambiguous results. For example, the effects of increases in income or the tax rate on reported income depend on properties of the taxpayer's utility function (e.g., relative risk aversion). It is always the case, however, that an increase in the probability of detection and conviction or an increase in the penalty rate will increase compliance.

The bulk of the remainder of the theoretical economics literature on tax compliance consists of extensions and refinements of Allingham and Sandmo's model. In most cases, however, the modifications produce more ambiguous results, not fewer. For example, making labor supply decisions endogenous obviates even the conclusion that increases in the probability of detection and conviction increase compliance.[2]

More recent theoretical innovations have attempted to move out of the decision-theoretic framework characteristic of the early tax compliance literature. Of particular interest here are the principal-agent models of Border and Sobel (1985) and Reinganum and Wilde (1986) and the game-theoretic model of Graetz, Reinganum, and Wilde (1986). In both of these approaches the IRS is allowed to act strategically, conditioning its audit rules on the information it receives from taxpayers. Thus the models yield predictions about the nature of the equilibrium audit rule used by the IRS as well as the equilibrium reporting rule used by taxpayers.

Whether the IRS should be included as a strategic actor in theoretical models of tax compliance is of more than technical interest. In assessing empirically the deterrent effects of audits, it is critical whether the IRS audit selection process turns on taxpayer compliance behavior. If it does, then any empirical specification meant to explain taxpayer compliance behavior which treats audit rates exogenously may be seriously misspecified. Furthermore, an incorrect presumption that

probabilities of apprehension and sanctions for underreporting of income can be taken as given may imply unhelpful policy responses. Thus, while models that incorporate the IRS as a strategic player in the tax compliance game, such as Graetz, Reinganum, and Wilde (1986), make precise predictions about the nature of both equilibrium auditing and income reporting rules, we will focus in this paper on the narrower questions of the deterrent effects of audits and their endogeneity.

3. EXISTING EMPIRICAL WORK

Much of the nonsurvey based empirical work on compliance with the tax laws reports attempts to measure aggregate noncompliance using macroeconomic data. Henry, who conducted a comprehensive review of this research in 1983, has cast serious doubt on the methodological soundness of all of the half dozen or so studies of this type. Our work is more microeconomic in orientation, as are those of Clotfelter (1983) and Witte and Woodbury (1985).

Clotfelter analyzed a data set collected originally as part of the 1969 IRS Taxpayer Compliance Measurement Program (TCMP). The TCMP consists of detailed audits of a stratified random sample of taxpayers. Each of these "line-by-line audits" results in an amount of income taxes due that is regarded by the IRS auditor as "correct." Differences between the auditors' determinations and the taxpayers' original reports are then related to tax return characteristics in order to develop a scoring mechanism (the "Discriminant Index Function," or "DIF") that can be used by the IRS to establish and refine its broader audit selection mechanisms.

There are, of course, weaknesses with TCMP data. For example, the TCMP audit procedure generally misses substantial amounts of unreported cash income, and it misses nonfilers altogether (Graetz and Wilde, 1985). Nevertheless, it is one of the best sources of data currently available for estimating noncompliance.

Normally TCMP data is aggregated in some fashion or another before being released to the public since the Internal Revenue Code prohibits the IRS from revealing information about individual returns. When Clotfelter wrote his paper he was an employee of the Treasury Department and was thus able to use the richer return information on income and tax deduction items as well as the estimates of noncompliance contained in the TCMP files. He therefore focussed on the relationship between marginal tax rates and tax evasion for three classes of taxpayers (nonbusiness, nonfarm business, and farm). For each group he estimated a single equation using Tobit maximum likelihood procedures. The dependent variable was the log of underreported income and the independent variables included a measure of the effective marginal tax rate, after-tax income, wages as a proportion of adjusted gross income, interest and dividends as a proportion of adjusted gross income, and several socio-demographic variables. The average audit rate for each taxpayer class was not included as an independent variable since, as Clotfelter put it, "the probability [of audit] for any tax return in a given class is a function of its reported items"; in other words, there is a potential simultaneity problem that makes it inappropriate to use audit rates as explanatory variables in an equation meant to explain compliance with the tax laws.

Clotfelter found that both the level of after-tax income and marginal tax rates have significant negative effects on compliance. In particular, his estimates suggest that a 10 percent decline in the combined federal and state marginal tax rate would result in a 5 to 8 percent decline in

underreporting. Elasticities of underreporting with respect to after tax income were .292, .620 and .656 for nonbusiness, nonfarm business and farm returns respectively. While Clotfelter's results are interesting, they should be used with caution. There are two main problems. First, Clotfelter tries to avoid the simultaneity issue by leaving audit rates out of his model. But if audit rates affect compliance then his model is still misspecified. This problem is especially acute with respect to income since audit rates certainly respond to reported income, but, because marginal tax rates are also correlated with income, it is likely to bias Clotfelter's estimates of the effects of marginal tax rates on underreporting as well. Moreover, the latter results depend on a particular way of constructing the marginal tax rate (see Clotfelter, 1983, footnote 10).

Witte and Woodbury (1985) do attempt to analyze the effects of audit rates and sanction levels on compliance. The data set used by these authors is virtually identical to the one we use in this paper and is discussed in detail in the next section. It includes an estimated percentage compliance variable related to 1969 returns filed in 1970 (but not based on actual IRS audits), IRS agency variables such as audit rates and sanction levels, and a host of demographic and socio-economic variables, all aggregated to the three digit zip code level. Separate equations were estimated by Witte and Woodbury for each of seven audit classes, defined by income level (low, medium, or high) and by type of return (1040 only, Schedule C or F present, Schedule C and F not present), using seemingly unrelated regression. In particular, for each audit class, the estimated 1969 percentage compliance variable was regressed on a constant term and 36 explanatory variables, including audit rates for 1967, 1968, and 1969 within the audit class, and for all other audit classes.

We discuss the 1969 IRS data set in detail in Section 4, but the two primary problems with the Witte and Woodbury analysis are (1) the numerical properties of the full 1969 data set make it undesirable to regress the estimated 1969 percentage compliance variable on all 36 of the other variables provided by the IRS,[3] and (2) many of the agency variables are likely to be endogenous in which case the model used by Witte and Woodbury is also misspecified.[4]

These problems perhaps explain some of the peculiar results obtained by Witte and Woodbury. In their published paper, for example, they report selected results for three of the seven audit classes. For these, audit classes reported mean elasticities of percentage compliance with respect to "audit rates" range from .002 to .02, approximately. However, by referring to their 1984 working paper, one finds first that these elasticities are obtained by summing the coefficients, when significant, on all six of the audit variables (1967, 1968, and 1969 audit rates within each audit class and for all other audit classes). Second, only one of the 1969 within-class audit rate variables is significant and it has a negative sign, six of the seven 1968 within-class audit rate variables are significant and half have a negative sign, and six of the seven 1967 within-class audit rate variables are significant but all have a positive sign. It is difficult, indeed, to conclude from these results that increases in audit rates increase compliance.

In summary, both the Witte and Woodbury and the Clotfelter analyses seem problematic. We intend to improve the Witte and Woodbury analysis by using only a subset of the 1969 IRS data set, augmenting it with additional variables, and allowing audit rates to be endogenous.

4. THE DATA

Our analysis is based on the 1969 IRS data set described briefly in the last section. We used eight variables from that data set, supplemented by five variables taken from the *Report of the Commissioner of Internal Revenue.* We describe the variables from the 1969 IRS data set first.

(i) *Estimated Voluntary Compliance* (*vcl*): Every two or three years since 1969 the IRS has conducted a special series of audits connected with the Taxpayer Compliance Measurement Program (TCMP) which are used in part to establish its audit selection mechanism. To this end, results of the TCMP audits are used to define a scoring rule. The scoring rule associates a number, called the DIF score, with each tax return, based on that return's characteristics. A higher DIF score on a given individual's return reflects a larger expected post-audit adjustment in the tax liability owed by that individual. To the extent that most such adjustments are in favor of the IRS, the DIF score thus reflects a so-called "yield criterion."

For each three-digit zip code and each audit class, *vcl* was constructed (by the IRS) by associating with every 1969 tax return in that zip code area and audit class, the absolute value of the expected adjustment in tax liability associated with the return's DIF score, denoted TC. For zip code area i and audit class j, the IRS then defined

$$vcl_{ij} = \sum_k SR_{ijk} / [\sum_k SR_{ijk} + \sum_k TC_{ijk}]$$

where SR_{ijk} is the actual self-reported tax liability of individual k in zip code area i and audit class j. Thus *vcl* is only indirectly related to the TCMP audits, but it includes all returns actually filed in calendar year 1970 for tax year 1969.[5]

(ii) *Audit Rates* (*audit*): This variable is defined as the percent of taxpayers filing a 1968 return in calendar year 1969 who were audited in calendar year 1968, for the audit class in the zip code area. It is *not* the audit rate as applied to 1969 returns.

The following six variables assume common values for all audit classes in a given zip code area.

(iii) *Unemployment Rates* (*uemp*): The percentage of the population 16 years of age and older who were unemployed in 1970.

(iv) *Percentage Nonwhite* (*nw*): The percentage of the population in 1970 who were nonwhite.

(v) *Percentage Manufacturing* (*manuf*): The percentage of total employed persons 16 years of age and older employed in manufacturing in 1970.

(vi) *Age* (*old*): The percentage of the population 65 years of age and older in 1970.

(vii) *Education* (*hseduc*): The percentage of the total population 25 years of age and older with at least 4 years of high school completed in 1970.

(viii) *IRS Investigative Activity* (*invest*): The total number of preliminary or full scale criminal fraud investigations initiated in fiscal year 1970 per 100,000 1968 returns filed in calendar year 1969.

The following five variables were taken from the 1969 Report of the Commissioner of the IRS. They take common values for all audit classes and all zip code areas within a state.[6]

(ix) *Occupational Stamps Issued* (*stamps*): The total number of occupational stamps issued in 1968.

(x) *Self-Employment* (*perself*): Income tax not withheld and self-employment tax as a percentage of total individual income and employment tax in 1968.

(xi) *IRS Resources* (*obper*): The total budget of all IRS district offices within a state for 1968 divided by the total number of returns filed in the state in 1968.

(xii) *Percent Individual Returns Filed* (*pirf*): The percent of all returns filed in 1968 that were individual income tax returns (as opposed to corporate, estate, gift, etc.).

(xiii) *Percent Excise Tax Returns Filed* (*pexf*): The percent of all returns filed in 1968 that were excise tax returns.

The explanatory variables we use in our specification of the compliance model are the 1968 within-class audit rate (*audit*), the unemployment rate (*uemp*), the percentage of nonwhite population (*nw*), the percentage employed in manufacturing (*manuf*), the percentage of the population over 65 (*old*), the percentage of persons over 25 with at least four years of high school education (*hseduc*), and the percent of collections not withheld or from self-employment taxes (*perself*).

The unemployment, manufacturing and self-employment variables are included as they reflect opportunities to evade. The nonwhite, age and education variables are included because other studies, primarily surveys, suggest they are important.[7] The audit variable, obviously, is expected to be related to compliance levels, but our analysis regards this variable as potentially endogenous. We test this hypothesis by using an instrumental variables procedure (described in Section 5). This requires that we find additional variables, or "instruments" which are expected to be correlated with audit rates but not with the unobserved factors which determine compliance. As instruments we use the number of criminal fraud investigations initiated in 1970 per 1968 return filed in 1969 (*invest*), the number of occupational stamps issued (*stamps*), the percentage of individual and excise tax returns filed (*pirf* and *pexf*) and the IRS budget per tax return filed (*obper*).

Invest is a candidate for an instrument since it is an IRS activity which is closely related to auditing but which does not have an obvious causal connection with the compliance behavior of taxpayers. Criminal fraud investigations are often instigated by third-party agencies outside the IRS, and, in any event, are only relevant to a very small percentage of taxpayers. Moreover, most of these investigations fail to lead to criminal charges and generally are handled by a special division within the IRS. The occupational stamps variable and the percent returns filed variables are related to the extent of competition for resources within the IRS. Our final instrument, the IRS budget per tax return filed, is a natural choice for an instrument since districts with larger budgets can afford more audits but variations in the budget are unlikely to be observed by, or have any appreciable effect on taxpayers.[8]

5. THE ESTIMATION

As we have noted already, the 1969 IRS data set is a pooled cross-section of 36 variables for seven audit classes. The audit classes are described in Table 1. Individual observations in each audit class represent aggregate values for geographic groups at the three digit zip-code level. Table 2 shows descriptive statistics for each of the 13 variables described above by audit class.

The relation to be estimated relates voluntary compliance (*vcl*) to 1968 audit rates and the various socio-economic variables:

$$vcl_{ij} = \alpha_{0j} + \alpha_{1j}\, audit_{ij} + \alpha_{2j}\, uemp_{ij} + \alpha_{3j}\, nw_{ij} + \alpha_{4j}\, manuf_{ij} + \alpha_{5j}\, old_{ij} + \alpha_{6j}\, hseduc_{ij} + \alpha_{7j}\, perself_{ij} + \eta_{ij} \quad (1)$$

where η_{ij} denotes a random disturbance for observation i within audit-class j. The coefficients, α_j, are not expected to be equal across audit-classes and are not constrained to be so in estimation. .PP Our estimation of equation (1) allows for the possible endogeneity of *audit*. Endogeneity occurs when elements of a taxpayer's income and tax status which are, of course, known by the taxpayer and observed by the IRS (but not by us) induce below average compliance and, simultaneously, induce greater audit rates. In this case, correlation between *audit* and the unobservables, η_{ij}, will lead to inconsistent estimates of the parameters using ordinary least squares estimation. Such correlation can occur for a variety of reasons. The theoretical construct which underlies our analysis suggests that audit rates should respond *directly* to compliance levels as well as compliance levels responding directly to audit rates. However, *audit* is based on audits performed in calendar year 1968 while *vcl* is an estimate of compliance on 1969 tax returns. Nevertheless, there may exist correlation between *audit* and unobservables which affect *vcl*. For example, there may be serial correlation in compliance behavior, or the IRS may have engaged in targeted audit activities during calendar year 1968 in anticipation of reduced compliance levels on 1969 returns filed in 1970.

In order to test for the endogeneity of *audit*, we employ a test due to Hausman (1978). This method includes as an additional explanatory variable the predicted value of *audit* derived from a reduced form in which the independent variables include those specified in (1) as well as the instruments. Hausman shows that endogeneity of *audit* is given by testing the significance of this additional explanatory variable. It is easily demonstrated that a consistent estimate of the coefficient of *audit* is given by the sum of the estimated coefficient of *audit* and the estimated coefficient of the predicted *audit* explanatory variable. This form of the Hausman test is equivalent to instrumental variables estimation.[9]

Table 3 presents the instrumental-variables estimates of these same equations.[10] At the bottom of Table 4 we calculate the Wald test for joint significance of all coefficients except the constant (variable "*one*"). The asymptotic distribution of this statistic is chi-squared with seven degrees of freedom (95% critical level equals 2.01). In each case, the overall fit of the model is impressive. In addition, in order to gauge the impact of colinearity in our explanatory variable matrix, we have calculated the condition number for the normalized data matrix.[11] These calculated condition numbers for our explanatory variables are well under 50 and do not indicate concern for colinearity.[12]

TABLE 1

AUDIT CLASS DEFINITIONS

Class	Number of Observations	Description
1	865	low-income (AGI < $10,000), nonbusiness with standard deduction
2	856	low-income, nonbusiness, with itemized deductions.
3	858	low-income, business
4	830	medium-income ($10,000 ≤ AGI ≤ $50,000), nonbusiness
5	801	medium-income ($10,000 ≤ AGI ≤ $30,000), business
6	569	high-income (AGI ≥ $50,000), nonbusiness
7	801	high-income (AGI ≥ $30,000), business

Total observations equal 5580. Business returns have schedule C or F present. Nonbusiness returns have neither schedule C nor F present.

TABLE 2

MEAN VALUES BY AUDIT CLASS
(Standard Errors in Parenthesis)

Variable	Class 1	2	3	4	5	6	7
vcl	96.57	92.63	81.55	97.05	90.78	94.41	90.58
	(1.36)	(1.11)	(2.36)	(0.35)	(1.60)	(1.32)	(2.22)
audit	1.14	2.51	2.71	3.68	4.16	11.20	9.75
	(0.41)	(0.74)	(1.09)	(1.07)	(1.62)	(4.36)	(4.07)
uemp	2.46	2.46	2.46	2.46	2.44	2.46	2.43
	(0.81)	(0.81)	(0.80)	(0.81)	(0.81)	(0.79)	(0.81)
nw	9.43	9.50	9.33	9.49	9.51	10.09	9.54
	(12.03)	(12.07)	(11.74)	(11.74)	(11.62)	(11.51)	(11.72)
manuf	23.10	23.21	23.14	23.48	23.71	25.79	23.67
	(11.49)	(11.45)	(11.41)	(11.33)	(11.23)	(10.77)	(11.20)
old	10.55	10.55	10.60	10.49	10.58	10.03	10.57
	(3.18)	(3.15)	(3.13)	(3.11)	(3.14)	(2.87)	(3.16)
hseduc	50.91	50.98	50.80	51.40	51.52	53.16	51.38
	(11.55)	(11.38)	(11.43)	(11.08)	(10.84)	(10.45)	(10.98)
perself	0.21	0.21	0.21	0.21	0.21	0.20	0.21
	(0.0537)	(0.0537)	(0.0538)	(0.0535)	(0.0537)	(0.0488)	(0.0533)
invest	56.22	56.81	56.64	55.49	53.90	37.99	53.29
	(73.64)	(73.80)	(73.79)	(67.20)	(63.06)	(38.95)	(60.13)
obper	0.00353	0.00352	0.00352	0.00352	0.00350	0.00352	0.00349
	(0.000978)	(0.000957)	(0.000925)	(0.000962)	(0.000921)	(0.000943)	(0.000922)
pirf	0.11	0.11	0.11	0.11	0.11	0.12	0.11
	(0.10)	(0.10)	(0.10)	(0.11)	(0.11)	(0.13)	(0.11)
stamps	0.028	0.028	0.028	0.029	0.030	0.035	0.030
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.030)	(0.028)
pexf	0.016	0.016	0.016	0.016	0.016	0.015	0.016
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0033)	(0.0039)

TABLE 3

ORDINARY LEAST SQUARES ESTIMATION (BY AUDIT CLASS)
DEPENDENT VARIABLE IS *VCL**

Variable	Class 1	2	3	4	5	6	7
one	93.97	93.20	76.70	97.41	87.90	94.72	88.98
	(245.83)	(267.08)	(109.35)	(785.23)	(165.00)	(150.43)	(109.16)
audit	-0.036	0.23	0.24	-0.035	0.21	-0.071	0.039
	(-0.39)	(5.34)	(3.70)	(-3.27)	(7.47)	(-6.34)	(2.32)
uemp	-0.21	-0.31	-0.70	-0.087	-0.18	-0.29	-0.68
	(-5.36)	(-8.51)	(-8.84)	(-6.60)	(-3.29)	(-4.70)	(-7.95)
nw	-0.036	-0.020	-0.025	-0.0042	0.032	-0.016	-0.014
	(-11.36)	(-7.40)	(-4.08)	(-4.14)	(7.37)	(-3.25)	(-2.09)
manuf	0.039	0.041	0.077	0.011	0.069	0.032	0.077
	(12.54)	(14.00)	(12.08)	(9.78)	(14.82)	(5.68)	(10.61)
old	0.053	-0.045	0.13	-0.0027	-0.0096	0.095	0.10
	(4.80)	(-4.26)	(5.84)	(-0.73)	(-0.62)	(5.33)	(4.15)
hseduc	0.054	0.0055	0.079	-0.00088	0.036	0.0013	0.0052
	(15.97)	(1.80)	(11.34)	(-0.76)	(7.02)	(0.23)	(0.67)
perself	-3.41	-4.58	-4.88	-0.75	-5.98	-2.44	-0.67
	(-5.19)	(-7.15)	(-3.69)	(-3.37)	(-6.52)	(-2.22)	(-0.46)
Number of observations	865	856	858	830	801	569	801
Corrected R-squared	0.54	0.41	0.39	0.27	0.41	0.25	0.23
Standard error of regression	0.92	0.86	1.83	0.30	1.22	1.15	1.94

*t-statistics are in parenthesis

TABLE 4

INSTRUMENTAL VARIABLES ESTIMATION (BY AUDIT CLASS)
DEPENDENT VARIABLE IS *VCL**

Variable	Class 1	2	3	4	5	6	7
one	90.90	92.97	76.94	97.72	88.64	97.06	107.13
	(53.82)	(190.19)	(103.58)	(614.12)	(130.33)	(86.86)	(10.25)
audit	1.78	0.33	-0.079	-0.16	-0.16	-0.31	-2.60
	(1.84)	(2.18)	(-0.27)	(-4.43)	(-0.94)	(-4.09)	(-1.90)
uemp	-0.20	-0.32	-0.70	-0.082	-0.18	-0.27	-0.89
	(-4.33)	(-8.42)	(-8.72)	(-5.75)	(-3.02)	(-3.22)	(-1.81)
nw	-0.058	-0.021	-0.019	-0.0039	0.038	-0.0091	-0.099
	(-4.64)	(-7.32)	(-2.54)	(-3.49)	(6.89)	(-1.29)	(1.42)
manuf	0.040	0.043	0.076	0.0078	0.068	0.030	0.10
	(10.57)	(12.78)	(11.84)	(5.30)	(13.18)	(3.92)	(2.41)
old	0.073	-0.041	0.11	-0.00044	-0.021	0.12	0.25
	(4.29)	(-3.26)	(4.18)	(-0.11)	(-1.15)	(4.65)	(1.59)
hseduc	0.076	0.0058	0.093	-0.0013	0.051	0.011	0.11
	(6.08)	(1.87)	(6.61)	(0.95)	(5.78)	(1.28)	(1.59)
perself	-4.25	-4.95	-4.49	-0.45	-5.41	-4.65	-3.46
	(-4.70)	(-5.83)	(-3.25)	(-1.76)	(-5.16)	(-2.84)	(-0.42)
Number of observations	865	856	858	830	801	569	801
Standard error of regression	1.10	0.86	1.86	0.33	1.35	1.54	10.88
Chi-square test for joint significance	724.35	564.32	535.80	283.60	417.29	100.10	11.47

*t-statistics are in parenthesis

Finally, we address the question concerning the endogeneity of *audit*. To form the predicted value of *audit* we estimate the reduced-form equations:

$$audit_{ij} = \gamma_{1j} + \gamma_{2j}\, uemp_{ij} + \gamma_{3j}\, nw_{ij} + \gamma_{4j}\, manuf_{ij} + \gamma_{5j}\, old_{ij} + \gamma_{6j}\, hseduc_{ij} + \gamma_{7j}\, perself_{ij}$$
$$+ \gamma_{8j}\, invest_{ij} + \gamma_{9j}\, stamps_{ij} + \gamma_{10j}\, obper_{ij} + \gamma_{11j} pirf_{ij} + \gamma_{12j} pexf_{ij} + \xi_{ij} \qquad (2)$$

This equation contains the maintained exogenous variables, *uemp*, *nw*, *manuf*, *old*, *hseduc*, and *perself*. It also includes the instrumental variables, *invest*, *stamps*, *obper*, *pirf*, and *pexf*. The results of least-squares estimation of equation (2) are presented in Table 5.

The Hausman statistic for the endogeneity of *audit* corresponds to a t-test for the significance of the coefficient on the predicted value of *audit* from equation (2) as estimated in equation (1). The estimated coefficients of both *audit* and predicted *audit* (*paudit*) are presented in Table 6. At the five percent significance level, endogeneity is found in audit classes 1, 4, 5, 6, and 7. The direction of bias is consistent across the audit groups except for audit class 1: ordinary least squares over-estimates the equilibrium relationship between audit rates and compliance. This leads to the false conclusion in three of the seven audit classes that, other things equal, increases in audit rates are associated with increases in compliance. These results are discussed in the next section.

6. RESULTS

Our results fall into two categories. The first has to do with the nature of the IRS audit process—whether it should be treated as endogenous—and the second has to do with the nature of the factors which influence equilibrium compliance and auditing behavior at the level of aggregation associated with our data set. We discuss first the endogeneity of the audit process.

As we indicated above, in five of the seven audit classes defined in the 1969 IRS data set, we find the audit rate to be endogenous. Given the level of aggregation of our data, and the fact that the measure of compliance included in the 1969 IRS data set is proportional (as opposed to absolute), we believe this to be impressive confirmation of an economic model of Federal Income Tax auditing and compliance which treats the IRS as an endogenous actor in the revenue collection process. Moreover, the nature of the endogeneity uncovered by our analysis is consistent with an interpretation in which the IRS concentrates its limited audit resources on those taxpayers for whom compliance levels are expected to be low, ex post (thus yielding high observed marginal revenue/cost ratios). This strategy should be contrasted with one in which the IRS precommits its limited audit resources to monitoring those taxpayers who are most likely to understate their income, ex ante, thereby inducing them to report more honestly (thus yielding low observed marginal revenue/cost ratios). In each of the four middle and upper income audit classes, all of which exhibit an endogenous audit rate, the observed (equilibrium) relationship between audit rates and percentage compliance was negative, producing the seemingly counterintuitive result that higher audit rates are associated with lower compliance levels. But once it is seen that the audit rate itself responds to compliance levels for these audit classes, a natural interpretation of these results is that the IRS's incentives to audit most heavily those individuals for whom actual compliance levels are expected to be low (what we call the "yield effect") dominates any deterrence effects of audits on individual

TABLE 5

REDUCED FORM ESTIMATES (BY AUDIT CLASS)
DEPENDENT VARIABLE IS *AUDIT**

Variable	Class 1	2	3	4	5	6	7
one	1.54	1.44	0.17	1.21	1.07	5.98	6.70
	(11.08)	(5.18)	(0.42)	(2.93)	(1.46)	(2.32)	(3.57)
uemp	-0.020	0.00019	0.0036	-0.070	-0.023	-0.27	-0.12
	(-1.33)	(0.0065)	(0.084)	(-1.60)	(-0.31)	(-1.05)	(-0.63)
nw	0.013	-0.0059	0.015	0.0047	0.017	0.036	0.046
	(11.79)	(2.77)	(5.00)	(1.46)	(3.01)	(1.87)	(3.18)
manuf	0.00039	-0.0045	-0.000060	-0.019	0.00091	0.0068	0.014
	(0.32)	(-1.86)	(-0.017)	(-5.18)	(0.15)	(0.31)	(0.84)
old	-0.012	-0.042	-0.051	0.013	-0.033	0.055	0.047
	(-2.93)	(-5.27)	(-4.49)	(1.13)	(-1.66)	(0.79)	(0.91)
hseduc	-0.014	-0.0060	0.039	0.010	0.038	0.015	0.043
	(-11.13)	(-2.39)	(11.23)	(2.62)	(5.67)	(0.65)	(2.49)
perself	0.56	3.81	2.30	4.02	3.07	-3.68	-0.45
	(2.08)	(7.16)	(3.00)	(5.19)	(2.34)	(-0.79)	(-0.13)
invest	-0.000021	-0.00013	-0.00093	0.0011	0.0016	0.0011	0.0031
	(-0.13)	(-0.39)	(-1.96)	(2.03)	(1.66)	(0.22)	(1.16)
obper	21.71	200.52	268.63	230.90	318.18	572.01	-125.52
	(1.53)	(7.03)	(6.33)	(5.56)	(4.32)	(2.35)	(-0.64)
pirf	0.094	-0.66	-0.60	-0.23	-0.87	1.92	-0.89
	(0.84)	(-3.00)	(-1.88)	(-0.72)	-1.67	(1.31)	(-0.65)
stamps	1.22	0.54	-2.5	9.4	-0.53	23.9	9.2
	(2.48)	(0.56)	(-1.78)	(6.74)	(-0.22)	(3.22)	(1.49)
pexf	6.80	25.72	-21.15	25.29	-26.10	107.72	6.61
	(1.73)	(3.31)	(-1.88)	(2.24)	(-1.37)	(1.51)	(0.13)
Number of observations	865	856	858	830	801	569	801
Corrected R-squared	0.35	0.23	0.26	0.24	0.10	0.04	0.004
Standard error of regression	0.33	0.65	0.94	0.93	1.54	4.27	4.06

*t-statistics are in parenthesis.

TABLE 6

ENDOGENEITY OF *AUDIT* (BY AUDIT CLASS)
DEPENDENT VARIABLE IS *VCL**

Variable	Class 1	2	3	4	5	6	7
audit	-0.061	0.22	0.26	-0.021	0.22	-0.061	0.052
	(-0.65)	(4.91)	(3.86)	(-1.84)	(7.81)	(-5.44)	(3.31)
paudit	1.84	0.10	-0.34	-0.14	-0.38	-0.25	-2.65
	(2.28)	(0.67)	(-1.14)	(-3.97)	(-2.43)	(-4.44)	(-11.71)

*OLS regression of *vcl* on *one*, *audit*, *paudit*, *uemp*, *nw*, *manuf*, *old*, *hseduc*, and *perself*. Coefficients reported are those of *audit* and the predicted value of *audit*, from Table 5, *paudit*. t-statistics are in parenthesis.

taxpayers in these cases.

Once endogeneity of the audit process is sorted out, we can see a rather striking pattern of effects. In the low income audit classes (1, 2 and 3), audits are positively related to compliance (this comes from the coefficient on *audit* in Table 4 for audit class 1 and Table 3 for audit classes 2 and 3). In the middle and high income classes, though, we see a nonpositive relationship between audits and compliance (in fact, the coefficient on *audit* in Table 4 is strictly negative for audit classes 4, 6 and 7, and negative but insignificant for audit class 5). Thus, for the low income classes we see a pure deterrent effect, but for middle and high income classes the yield effect dominates (in equilibrium). This contrasts sharply with the results one would have obtained using ordinary least squares (i.e., ignoring the potential endogeneity of audit rates). In the latter case, one observes a totally spurious deterrent effect of audits in classes 5 and 7, and substantially overestimated deterrent effects in classes 4 and 6. It is clear from these results that ignoring endogeneity can be a very serious problem.

Of course, we also have a number of results related to the specific variables used in our model of the auditing and compliance game. We discuss next those factors besides audits which affect compliance, using the results of the ordinary least squares specification for audit classes 2 and 3, and those of the instrumental variables specification for audit classes 1, 4, 5, 6, and 7.

The two variables associated with opportunities to evade operate uniformly and consistently across all audit classes: an increase in the percent employed in manufacturing or a decrease in the self-employment variable increases percentage compliance in all cases except for the self-employment variable in audit class 7 (which is insignificant). Similarly, an increase in the unemployment rate uniformly decreases percentage compliance. This could be because individuals "compensate" for the lower income associated with spells of unemployment by understating a higher fraction of their actual income (a kind of "target-income" theory) or because they shift to various kinds of underground employment.[13] Increases in the percentage of nonwhites decrease compliance for low income audit classes and the middle income non-business audit class, but increase compliance for the middle income business audit class and have no effect on either high income audit class. Finally, we observe somewhat weaker results for the education and age variables. The latter is insignificant for middle income and high income business taxpayers, and generally positively related to compliance for others (except for low income taxpayers who itemize—for them it is negatively related to compliance). The former is positively related to compliance whenever it is significant (audit classes 1, 3, and 6).[14]

Our results with respect to the auditing process are much more mixed, although some consistent patterns emerge. An increase in the district (or state) budget per return generally yields more audits (except in audit classes 1 and 7). Unemployment rates are totally irrelevant to the auditing process, the percent employed in manufacturing almost so (except for middle income nonbusiness returns where it is negatively related), and criminal fraud investigations scarcely better. On the other hand, the percentage of nonwhites is positively related to audits for five audit classes (1, 2, 3, 5 and 7), as is age for all three low income audit classes. Furthermore, household education is negatively related to audits for low income nonbusiness returns but positively related to audits for all three classes of business returns. Finally, percent self-employed is positively related to audits for low and middle incomes and insignificant for upper income classes.

The mixed performance of the audit equations should perhaps not be too surprising. IRS audits turn directly on the DIF score assigned to individual returns. The DIF score, however, depends only on tax return characteristics. Thus there is no particular reason why audits should track socioeconomic characteristics of the population independently of the indirect effects of these characteristics on compliance.

A final set of results has to do with the effects of income on compliance. Since our data set was segmented by audit class, which explicitly includes income, we did not include an income variable directly in our regressions. However, we can calculate an income effect by performing the following experiment. Move an average audit class i individual into audit class j. Using the estimated coefficients in equation 1 for class j, we calculate a new predicted compliance level. The change in compliance from audit class j's base value is attributable to the change in income (and filing status, etc.). These calculations are given in Table 7 for business returns and in Table 8 for nonbusiness returns.

Consider first Table 7, which describes business returns. The first row should be interpreted in the following way. The average low income business taxpayer has a voluntary compliance level of 81.55 percent. If that taxpayer acted as though he had medium income, he or she would have a voluntary compliance level of 90.92 percent. Acting like a high income taxpayer, this figure would rise further to the maximum level. Similar patterns emerge for medium and high income taxpayers (except that there is virtually no effect when the average high income taxpayer acts as though he or she had medium income). These results mean that *in equilibrium*, compliance increases with income, at least with respect to business returns.

A somewhat different pattern emerges in Table 8, which deals with nonbusiness returns. Here (ignoring audit class 1—low income, standard form returns) compliance has an inverted u-shape, peaking with medium income; there is a sense in which compliance is lowest for low and high income groups. This pattern of behavior apparently is consistent with survey results due to Mason, Calvin and Faulkenberry (1974) and Mason and Lowry (1981), (as described by Witte and Woodbury, 1983).

7. CONCLUSION/SUMMARY

Our analysis of the 1969 IRS cross-section data set has yielded a number of strong results. While audits have a deterrent effect on noncompliance, they respond, at least for middle and upper income levels, to the pattern of noncompliance—the IRS seems to direct its resources to those areas in which compliance is the worst. In fact, this effect is so strong we generally see negative relationships between auditing and compliance (in equilibrium) for those cases in which audits are endogenous.

We also find that several socioeconomic factors, which tend to have no direct impact on auditing, have dramatic effects on compliance. For example, increases in the unemployment rate have significant "hidden costs" in the form of reduced compliance levels. Increases in the percentage of the nonwhite population also reduce compliance for low and middle income audit classes. These kinds of results are encouraging; they provide strong support for the economic approach to the compliance problem and suggest that the payoff to improved data and further analysis could be very

TABLE 7

PERCENT COMPLIANCE BY INCOME GROUP
BUSINESS RETURNS
MEAN AUDIT CLASS (*VCL*)

Mean Characteristics of Individuals in Audit Class	Compliance by Audit Class* 3	5	7
3	81.55	90.92	**
5	81.56	90.78	**
7	81.11	89.87	90.58

*Percentage compliance calculations are based on the instrumental variables estimates presented in Table 4.

**These estimates exceed the upper bound on compliance levels (100 percent).

TABLE 8

PERCENT COMPLIANCE BY INCOME GROUP
NONBUSINESS RETURNS
MEAN AUDIT CLASS (*VCL*)

Mean Characteristics of Individuals in Audit Class	Compliance by Audit Class* 1	2	4	6
1	96.57	92.18	97.45	97.44
2	99.02	92.63	97.23	97.01
4	**	93.04	97.05	96.67
6	**	95.67	95.87	94.41

*Percentage compliance calculations are based on the instrumental variables estimates presented in Table 4.

**These estimates exceed the upper bound on compliance levels (100 percent).

high. Moreover, they are consistent with preliminary results we have obtained using a state level, time-series cross-section data set assembled in part from the Annual Report of the Commissioner of Internal Revenue (Dubin, Graetz and Wilde, 1987), a fact which is also encouraging.

FOOTNOTES

* We would like to thank Bill Lefbom, Chairman of the TCMP committee of the IRS, for providing us with the 1969 IRS cross-section data set and helping us decipher it. Helpful comments have been provided by Dave Grether, Tom Gilligan, Rod Kiewiet, and especially Michael Graetz. This paper is a substantially revised version of Dubin and Wilde (1986).

1. Schedule C is for nonfarm business income and schedule F is for farm business income.

2. For a general model which incorporates labor supply decisions see Sandmo (1981); for recent surveys of the literature see Witte and Woodbury (1983) or Cowell (1985).

3. We discuss this problem and how we deal with it in detail in Section 5 below.

4. This is the same problem encountered by Clotfelter. Besides audit rates, Witte and Woodbury include a number of IRS related variables such as the frequency and level of imposition of sanctions, both civil and criminal, the level of data processing efforts, etc.

5. Details of this procedure are described in Borman (1978), a copy of which was generously provided to us by Ann Witte. Borman gives two examples of the estimated relationship between compliance levels and DIF scores for 1969. For audit class 1 (low income, nonbusiness, standard deduction) he reports

$$TC = 17.4868744(10.0049515^{DIF})$$

and for audit class 2 (low income, nonbusiness, itemized deductions)

$$TC = 49.4077759 + .2348477\,(DIF) + .0002691\,(DIF)^2.$$

6. The Annual Reports are organized by IRS "district." New York state has four districts, and California, Illinois, Ohio, Pennsylvania and Texas each have two districts. We aggregated these to the state level since we could not link three-digit zip codes to districts smaller than the state level.

7. See Witte and Woodbury (1983) or Cowell (1985) for reviews of this literature.

8. It is, in principle, possible that *obper* responds over time to compliance levels. We have analyzed the time path of IRS budgets and find them to be largely determined by total returns filed and only weakly related to compliance.

9. Let $x = Z\gamma + \nu = Z_1\gamma_1 + Z_2\gamma_2 + \nu$ where Z_1 is an $N \times K_1$ matrix of endogenous variables, Z_2 is on $n \times K_2$ matrix of exogenous variables, $Z = [Z_1 \vdots Z_2]$ and $W = [W_1 \vdots Z_2]$ is a $N \times (p + K_2)$ matrix of instruments. Let $P_W = W(W'W)^{-1}W'$ and $M = I - P_W$. Then $\hat{\gamma}_{LS} = (Z'Z)^{-1}Z'x$ and $\hat{\gamma}_{IV} = (Z'P_wZ)^{-1}(Z'P_wx)$. Form the predicted endogenous variables as $\tilde{V} = P_WZ_1$ and the residuals from the reduced form as $V = MZ_1$. Hausman's method focuses on the equation $x = Z_1\gamma_1 + Z_2\gamma_2 + V\alpha + \nu_0$. It is straightforward to verify that ordinary lest-squares on this equation is equivalent to instrumental variables. Rewriting we have, $x = Z_1\gamma_1 + Z_2\gamma_2 + (Z_1 - P_WZ_1)\alpha + \nu_0 = Z_1(\gamma_1 + \alpha) + Z_2\gamma_2 + (P_WZ_1)(-\alpha) + \nu_0$. Thus the true coefficient γ_1 is the sum of the coefficients of Z_1 and P_WZ_1.

10. Equation (1) may be estimated equation by equation, i.e. by audit-class, or in a seemingly-unrelated regression system. The later method is appropriate when the covariance structure of the unobservables suggests inter-equation correlation. Using a system estimation method in this context however requires a common set of observations (or zip-codes) from each audit-class. This approach severely reduces the available observations. A balanced sub-sample of the IRS data requires the loss of 1611 (5580-7*567) observations — over 25 percent of the sample. While seemingly unrelated regression techniques are programmable they are not readily available for unbalanced equation systems with endogenous explanatory variables. The efficiency gains from the additional observations almost surely out weigh those gained from inter-equation correlation and thus we employ a single-equation estimation technique. With respect to pooling across audit classes, inferences based on the subset of common observations lead us to reject the equality of coefficients.

11. Let X be any $n \times p$ matrix, considered here to be a matrix of n observations on p variables. Then X has a unique decomposition, $X = UDV^T$ where $U^TU = V^TV = I$, and D is diagonal with nonnegative elements μ_k, $k = 1,2,...,p$, (the singular-values of x). Note that $X'X = VD^2V^T$ so that $(X'X)^{-1} = VD^{-2}V^T$. Singularity or near singularity in $X'X$ manifests itself when D^{-2} is formed. Near zero elements of D will cause the inverse of $(X'X)$ to be unstable. Belsley, Kuh, and Welsch (1980) define a condition index for the matrix X by its spectral norm, the ratio of μ_{max} to μ_{min}. For the purposes of comparing arbitrary matrices X, Belsley, Kuh, and Welsch recommend scaling the columns so that they have unit length. Condition numbers in the range of 50 to 100 indicate severe colinearity. For further details, see Belsley, Kuh, and Welsch (1980).

12. The condition numbers for our data set range from 33 to 39. These are based on regressions with 8 variables and roughly 800 to 850 observations. By contrast, the condition numbers for regressions based on all 36 variables included in the 1969 IRS data set, as used by Witte and Woodbury (1985), range from 370 to 400 (using 567 observations). The latter indicate severe ill-conditioning (Belsley, Kuh, and Welsch, 1980).

13. That *manuf* and *uemp* operate uniformly across all seven audit classes suggests that they may in part proxy regional effects. Unfortunately, the cross-sectional nature of this data set makes it impossible to identify to what extent they do so. The data set constructed by Dubin, Graetz and Wilde (1987) should help sort out this issue.

14. That age is positively related to compliance is consistent with Clotfelter's (1983) estimates and Spicer and Lunstedt's (1976) survey results. That compliance increases with education is consistent with Song and Yarbrough's (1978) survey but not the work of Mason and his colleagues (1975, 1981).

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