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Econometric Models for Multi-Stage Audit Processes: An Application to the IRS National Research Program[*]

Preliminary Working Draft: DO NOT CITE OR QUOTE WITHOUT PERMISSION FROM THE AUTHORS

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Abstract. We develop an econometric methodology to control for errors in assessments that result from multi-stage audit processes. We then apply our methodology to data from a random sample of individual income tax audits collected under the Internal Revenue Service's National Research Program to assess the extent to which noncompliance is successfully identified on various income line items of the tax return.

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I. Introduction

In this paper, we develop an econometric methodology to control for errors in assessments that result from multi-stage audit processes. We then apply our methodology to data from a random sample of individual income tax audits collected under the Internal Revenue Service's National Research Program (NRP) to assess the extent to which noncompliance is successfully identified on various income line items of the tax return.

Auditing is a standard and essential tool for assessing the validity and reliability of information and processes. Three of the most common forms of audit are financial, operational, and compliance. Financial audits are used to verify the accuracy of financial statements of governments and businesses. Operational audits are employed to assess managerial performance through an analysis of the effectiveness and efficiency of the operational structure, internal control procedures, and processes. Compliance audits are used to evaluate whether, and to what extent, policies, procedures, and other requirements for individuals, businesses, or organizations are being met. Compliance audits are frequently conducted by governments. Examples include examinations of tax returns; audits to assess compliance with regulatory policies, such as environmental regulations; and audits to evaluate whether reporting, spending, and other requirements are being met with respect to government-funded programs.

A common feature of these various forms of audit is that they normally seek only to provide reasonable assurance. Due to practical constraints, it is often infeasible to exhaustively examine every detail or aspect of an operation, system, or report. Hence, audits normally rely on sampling and testing, either at random, or in areas deemed to be of greatest risk for substantial noncompliance with reporting, procedural, or other requirements. Moreover, even when an issue or process is evaluated, there is often potential for imperfect detection of noncompliance. For example, in tax audits, examiners are not always successful in uncovering certain forms of income that have been understated. Thus, audit findings are frequently subject not only to sampling errors, but also errors in detection. In this paper, we introduce some econometric methods for controlling for such errors when analyzing the results of audits, and we apply these methods to a sample of individual income tax audit results to develop estimates of detected and undetected levels of tax noncompliance. Our approach is based on the detection controlled methodology introduced by Feinstein (1990, 1991), which we have adapted to account for the multi-stage nature of the tax return examination process.

Typically, audit processes involve several stages, and it is important to account for impact of the decisions made during these stages on the outcome of the audit. In our tax audit application, some of the key decisions made during the audit include: which returns to audit; the type of audit to be conducted; the classification of mandatory issues to be examined; and whether additional non-classified issues should be examined. These decisions are made at different stages of the process, and by different individuals. In particular, selection of returns for audit is conducted early in the process according to a stratified random sampling design. Under this design, returns considered at higher risk of noncompliance are subject to a higher sampling rate. Once selected, a return is assigned to a "classifier" who assesses what type of audit should be conducted (accept as filed; correspondence audit involving only one or a few issues; or a more intensive face-to-face audit). The majority of returns in our data were subjected to a face-to-face audit, and it is these returns that are the focus of our analysis. For such returns, the classifier is responsible for selecting a set of mandatory issues to be audited. At the examination stage, the examiner has discretion to audit additional issues on the return that have not been classified.

Our work builds on an earlier model that we developed to assist the IRS in estimating the aggregate tax reporting gap associated with federal individual income tax returns. The current framework extends our earlier work down to a more detailed level of analysis at the level of individual income components, focusing on estimating noncompliance associated with these income components. It is hoped that the resulting estimates from this approach will serve as key inputs for a microsimulation model of individual income tax reporting noncompliance under development by the IRS. The IRS has a sophisticated tax calculator that can be used to combine our estimates of income underreporting by income component with separate estimates of noncompliance with respect to deductions, credits, and other offsets for each return, generating estimates of tax reporting noncompliance by income component.

For our analysis, we rely on the Internal Revenue Service's National Research Program. In this important initiative, the IRS gathers data about tax noncompliance through stratified random sample of approximately $45,000$ federal individual income tax returns that have been subjected, in most cases, to rather substantial audits. The initial wave of NRP data is for tax year 2001. (For more background see Brown and Mazur (2003)).

We develop a suite of models, each tailored to a given set of income items. The NRP uses a classification process as a first stage in the examination process, in which a classifier determines whether a given line item or schedule should be intensively reviewed during the audit. For certain items, including those for which income is primarily covered by information reporting (examples include wages, interest, and dividends), this classification screening stage is quite important. For such items, third party information documents often provide a very strong indication of how much should be reported on the return. In many cases the amount reported by the taxpayer for such an item is consistent with what is shown on the information documents, obviating the need to perform a detailed examination of the item. Typically, then, such an item is classified for examination only when the reported amount is inconsistent with what is shown on third party information documents, when those information documents appear to be incomplete or suspicious, or when other available information points to a potential problem with the line item. For income items for which classification is an important screening process, we develop a model that includes an equation describing the classification process, thus extending the detection controlled model in a new direction that reflects the NRP examination process.

In contrast, there are other income items in the NRP that are routinely classified for a careful examination. For instance, in the great majority of cases where a tax return reports income from a nonfarm or farm sole proprietorship, the relevant schedule (Schedule C or Schedule F) is classified for examination. In cases like these where classification is fairly routine, it is not productive to model the classification process. In such cases, we therefore estimate a specification for the line item that does not include a classification equation.

A challenging issue for empirical estimation is those cases in which an examiner audits an income item that was not classified for examination. In the case of income items subject to extensive information reporting, it sometimes happens that an item is not classified for examination, but the examiner nonetheless thoroughly investigates the item, sometimes uncovering significant misreporting. We suspect that this typically happens when the examiner has uncovered some trace or signal that the income item may have been misreported during the course of his audit, which drives him to explore the issue more thoroughly. To address such cases, we model the examiner's decision to examine an income item that has not been classified for examination using a simple exponential model in which his chances of examining the issue are dependent on the level of noncompliance.

Our logic is that when noncompliance is present it is more likely the examiner will get a signal indicating the presence of noncompliance, triggering him to examine the item. We are in the process of developing and estimating a more structural model of this process, in which we model the examiner's decision more explicitly as a choice problem. We hope to present this model and results in a subsequent paper.

For income items not subject to extensive information reporting, it is often the case that an item is not classified for examination when the item has not been reported on the return. However, examiners sometimes do perform a careful examination of such an item even though it has not been reported or classified for examination. For example, there are many returns that do not report any income from a sole proprietorship, and the majority of these returns are not classified to have a detailed examination of this form of income. However, the NRP examiners do frequently perform some probing for self-employment income during their audits, and this sometimes leads to the identification of unreported Schedule C or Schedule F income. To account for such cases, we specify a separate detection process for unreported income items. Our specification includes one equation that describes the likelihood that the income item should have been reported and a second equation that describes the likelihood that the examiner discovers this fact in the course of his audit. The specification also accounts for the magnitude of the adjustment when noncompliance on the line item is discovered.

The model we present provides a richer framework for econometric analysis of audit and compliance systems than previous models, which often overly simplify the steps involved in selecting cases and issues for intensive examination. In particular, we believe many real-world enforcement systems grapple with the issues of different kinds of items being reported, and have multiple layers of evaluation. We note that our models do not address the full range of behavioral issues that arise in these systems. In particular, the models have not been derived from a specific game-theoretic, utility maximization framework. Nor do they account for factors such as social norms and preferences. Still, our framework describes the NRP classification and examination process with some care, recognizing that the process is different for different elements of the tax return and has multiple stages, and incorporates a relatively simple, standard semi-structural model of taxpayer behavior. We believe the framework offers a good foundation for developing a next generation of models, that may incorporate both the kinds of process level detail we include and more structured behavioral models of taxpayer reporting.

Our preliminary estimates document considerable heterogeneity in detection rates across examiners, a finding consistent with earlier work, for example by Feinstein (1989, 1991), Alexander and Feinstein (1987), and Erard (1993). In addition, these estimates indicate that the NRP classification process is generally effective in targeting items for examination. However, when examiners choose to examine items not classified, they do in some cases uncover significant noncompliance, indicating that classification is not always able to pick up on noncompliance that an examiner can discover during the exam. Our results also indicate that the yield on classification-guided examinations is not substantially different from the yield on audits for which examiners are instructed to perform a very thorough examination – a stratified random subsample of the NRP known as the "calibration sample."

As our preliminary results have not yet been formally reviewed by the IRS, we are not able to present most of our empirical results, in particular those pertaining to noncompliance, in this paper. Thus we do not present either the variables we include in our noncompliance expressions, the parameter estimates associated with those variables, or the implied levels of noncompliance (detected and not detected). Once our results are carefully reviewed we are hopeful we will able to make a fuller set of results public, in a subsequent paper.

The remainder of our paper is organized as follows. In section II we describe the NRP. In section III we present our model of taxpayer reporting and NRP classification and examination processes, derive the likelihood functions we estimate, and discuss estimation issues we encountered and modifications to our base model. In section IV we present empirical results. In section V we present our estimates of the tax gap and compare these with previous estimates. Section VI is a conclusion.

II. The NRP

The NRP database contains a stratified random sample of approximately $45,000$ federal individual income tax returns from tax year 2001 that were subjected to special examination procedures. An important feature of the data acquisition process is that not all cases follow the same pathway for data collection. There are in particular five features of the data acquisition process that are important for analysis, which we discuss in turn.

First, returns are subject to a classification process. In this process a classifier examines the filed return and places the return in one of three categories: (i) accepted – meaning the return is accepted as is or with minor adjustments, and, importantly, there is no further contact with the taxpayer (except if the return is then selected into the calibration sample – see below); (ii) correspondence audit – meaning a correspondence will be initiated with the taxpayer regarding a relatively circumscribed set of issues for which adjustments may be made – but there is no planned face-to-face audit; and (iii) audit – a face-to-face audit. The breakdown of cases into these 3 categories is approximately: $2,600$ accepted; $2,600$ selected for correspondence audit; and the balance, approximately $40,000$, selected for face-to-face audit. As mentioned above, we focus in our analysis on returns in category (iii) – the vast majority of returns in the NRP sample, and the returns for which aggregate noncompliance, on a weighted basis, is far and away the greatest.

Second, for returns in categories (ii) and (iii) the classifier flags a set of issues for either correspondence, in the case of returns falling in category (ii), or examination during audit, for returns falling in category (iii). Classification may be triggered by a variety of factors. As one example, a classifier will generally assign an issue for audit in cases in which a third party report indicates the presence of income not reported by the taxpayer. In cases where a taxpayer reports self-employment income, the classifier normally will assign various issues on Schedule C or Schedule F to be investigated, because noncompliance is known to be prevalent on these schedules. We discuss how we model this classification process in the next section.[1]

Third, a subset of cases is chosen for the "calibration sample." The calibration sample includes approximately 450 returns originally assigned to be accepted as filed from the ordinary NRP sample as well as approximately $1,200$ randomly selected returns that were not included in the ordinary NRP sample. Generally, returns assigned to the calibration sample receive a more thorough audit than they were initially assigned to receive. The calibration sample is a stratified random sample covering all three classification categories. We are in the process of using use the calibration sample to help identify certain

[1] We note that NRP classifiers had available additional various 'case-building' information, drawn from a variety of sources, both governmental and non-governmental. Some of these sources include third party information returns, previous year tax returns, IRS activity with respect to the taxpayer over the preceding several years, and a credit history. This information is placed on the NRP data record for the case – though the precise use made of it by the classifier is not recorded. We do make use of the third-party information return records in building our models, but we do not make use of other case-building information. The role of this additional information in the classification and audit process is an area for future research.

parameters in our models, but have not yet completed this work.

Fourth, during a face-to-face audit examiners have discretion to go beyond the issues flagged for examination during the classification process. In fact, the NRP data records show that examiners do investigate unclassified issues on some occasions. Indeed, examiners frequently probe for sources of income not reported on the return, even when that specific income source has not been classified. More generally, as an examiner conducts his audit, he may become suspicious of or uncover evidence to suggest potential noncompliance on an unclassified issue. In such cases, it is not uncommon for the examiner to discover significant noncompliance with respect to the issue. Importantly, the NRP data record issues that were examined, which of them were classified, and any adjustments that were made as a result of the examination.

Fifth, with respect to issues examined during a face-to-face audit, the examiner is supposed to record a zero when an issue has been audited but no misreporting has been identified. This is important in making a clear distinction in the data between issues examined for which no noncompliance is found and issues not examined.[2]

By allowing for multiple intensities of interaction with and levels of audit of taxpayers, the NRP sample design deviates significantly from that of the predecessor Taxpayer Compliance Measurement Program (TCMP), which called for uniformly intensive face-to-face examinations. To properly analyze the NRP, it is therefore necessary to develop and apply new models that account for these differences in sample design and examination procedures.

In our empirical estimation we use only returns subject to face-to-face examination and do not use returns that were subject either to a correspondence audit or accepted as filed. In restricting our attention to face-to-face examinations, we exclude approximately 5,200 returns. When weighted, these returns represent approximately 38 percent of the overall return population. Nonetheless, our analysis of the calibration sample suggests that this portion of the population is responsible for only a very small share of aggregate noncompliance in the population.

[2] For all issues for which non-compliance is discovered, the examiner is supposed to record the reason, as far as he can determine it, for the noncompliance, using a supplied list of reasons and the reason code. We do not use this information in our analysis.

III. Issues for Estimation

There are three fundamental factors that must be addressed when developing models of tax noncompliance and its detection in the NRP. These are: (1) heterogeneity in reporting behavior, particularly that there are unusually high levels of under-reporting by a small proportion of taxpayers; (2) the failure of the examination process to completely identify all cases of noncompliance; and (3) the NRP examination process itself, which has a specific structure.

Our models of taxpayer reporting behavior follow our earlier work (see for example Alm, Erard, and Feinstein (1996)). For many specifications we model reported noncompliance as a displaced log-normal distribution. The log-normal specification allows for a skewed distribution in which there is a "long tail" to the right of the distribution. This captures the empirical fact that there is a small proportion of taxpayers with very high levels of noncompliance. The displacement of the distribution allows us to account for the nontrivial percentage of taxpayers who fully and accurately report their tax liability. In some cases we also break the noncompliance decision into two parts: the first part is a simple probit model used to estimate the probability a household underreports, and the second part is a log-normal regression that estimates the magnitude of under-reporting conditional on under-reporting having occurred.[3]

Nondetection arises whenever the examiner fails to detect all noncompliance on a return. In the NRP this may happen for two distinct reasons: (1) the examiner fails to detect all noncompliance on an issue he examines; or (2) the examiner fails to audit an issue on which noncompliance exists. We model nondetection of the first kind using the detection-controlled methodology developed by Feinstein (Feinstein (1990, 1991)) and used also in Erard (1993) and in a variety of applications in other domains, including regulation and health care. We employ in particular the fractional detection model developed in Feinstein (1991). We model the second form of nondetection using the calibration sample as well as models that extrapolate from noncompliance found on returns examined for a specific issue to likely noncompliance for the same issue on returns for which the issue was not examined. As we discuss in our results section this extrapolation is empirically challenging to do in a sensible way, in part because when an examiner chooses to examine

[3] We do not model the taxpayer's reporting decision as a utility maximization problem nor as an optimal decision under some comparable structural model. Rather, we focus structurally on the enforcement side.

an issue that was not classified for examination it is often because he has a lead of some kind that points to potential noncompliance. As a consequence, detected noncompliance on unclassified issues that are ultimately examined tends to be relatively high, and we cannot simply assume that the rate of noncompliance is comparable on returns for which examiners do not have a lead and do not examine the issue. We develop specific modeling strategies to address this problem.

As discussed in the previous section, the NRP examination process has multiple stages and forms. We model the basic stages of classification and examination, and in the examination stage model separately detection on issues classified for exam and issues not classified for exam. We are in the process of developing richer, structural models of these processes which we will present in a companion paper.

IV. Models

In this section we present the main models we estimate. First we present our model of classification, noncompliance, and detection, which we view as novel and important for analyzing the NRP. Then we present the modified detection-controlled model we use for items for which classification is not modeled.

Model 1: Noncompliance, Classification, and Detection

Our model of noncompliance, classification, and detection consists of three equations. The first equation is a model of household noncompliance:

$$ln(N^* + h) = {\beta_N}' x_N + \epsilon_N \tag{1}$$

In this expression N^* is a latent variable describing the household's propensity to commit noncompliance on this particular issue. (Note that we do not subscript the issue for ease of notation.) The variable h is a displacement parameter that allows the distribution of N^* to extend below zero – h is required to be greater than or equal to zero; x_N are variables associated with household noncompliance, such as filing status, β_N is a vector of parameters, and ϵ_N is a random disturbance, discussed further below.
The actual level of noncompliance N is determined as:

$$N = \begin{cases} N^* & N^* > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

The classification process for this issue is determined as:

$$C^* = {\beta_C}' x_C + \epsilon_C, \tag{3}$$

In this expression C^* is a latent variable describing the propensity of the classifier to assign the issue to be examined, x_C are variables associated with the classification decision, β_C is a vector of parameters, and ϵ_C is a random disturbance. We observe the classification outcome C, where

$$C = \begin{cases} 1 & C^* > 0 \\ 0 & C^* \leq 0. \end{cases} \tag{4}$$

In our empirical specification we include a dummy for the identity of the classifier, for all classifiers who classify at least 20 returns, thus are able to test for differences in classification styles across classifiers. C is the actual classification decision: $C = 1$ means the issue is classified for examination.

We assume that the examiner always examines the issue if it has been classified for examination. It is also possible that the examiner will choose to examine the issue even if it has not been classified for examination. If the income component has not been assigned, we assume that the examiner elects to review it with probability:

$$\frac{exp\{\alpha_0 + \alpha_1 N\}}{1 + exp\{\alpha_0 + \alpha_1 N\}}. \tag{5}$$

In other words, we allow the examination probability to depend on the magnitude of actual noncompliance. We assume that the data do allow us to distinguish whether an unclassified income component with zero recorded noncompliance has been examined.[3]

Conditional on the examiner examining the issue, the detection process is modeled as:

$$D^* = {\beta_D}' x_D + \epsilon_D. \tag{6}$$

[3] We note that there is an identification issue here; subsequent work will incorporate the calibration sample to aid in identifying the model.

In this specification D^* is a latent variable describing the extent to which noncompliance is detected during the examination. The actual detection rate is D, which is the fraction of noncompliance on the issue that is detected, is defined as follows:

$$D = \begin{cases} 1 & D^* \geq 1 \text{ (complete detection)} \\ D^* & 0 < D^* < 1 \text{ (partial detection)} \\ 0 & D^* \leq 0 \text{ (nondetection).} \end{cases} \tag{7}$$

Our model of detection here is the fractional model introduced by Feinstein in his 1991 paper (Feinstein (1991)).

We assume that ϵ_N and ϵ_C are bivariate normally distributed, with zero means, standard deviations of σ_N and 1, respectively, and correlation coefficient ρ. For simplicity, we assume that ϵ_D is independent of ϵ_N and ϵ_C, and that it is normally distributed with mean zero and standard deviation σ_D. The assumption regarding ϵ_N implies that the propensity to commit noncompliance follows the displaced lognormal distribution. Such a distribution has a long and thin tail, consistent with empirical evidence that tax noncompliance tends to be highly skewed.

Likelihood Function for Model 1

As discussed in the previous section, there is an important problem of nondetection that arises in analyzing the NRP and indeed nearly any audit data. Not all noncompliance is detected, and we have no direct information about noncompliance that the examiner failed to detect. Our likelihood function thus centers around not the true level of noncompliance N, but rather the detected, assessed amount of noncompliance, which we denote A. Thus the likelihood function involves the joint distribution function of the two variables A and C, worked out in terms of the underlying model processes and the underlying variables N, D, and C. Further, we note that in transforming the likelihood from the variables N, D, and C to the variables A and C we introduce the Jacobian term $\left|1/D\right|$.[4]

The likelihood function consists of 5 distinct cases: (1) the issue is classified for exam and there is no detected noncompliance, $C = 1,\ A = 0$; (2) issue classified, noncompliance detected, $C = 1,\ A > 0$; (3) issue not classified for exam, issue examined anyway with no detected noncompliance, $C = 0, exam,\ A = 0$; (4) issue not classified, issue exam-

[4] In the course of our work on this project we discovered that Feinstein does not include this Jacobian term in the likelihood in his 1991 paper, a lacuna in his analysis.

ined, noncompliance detected, $C = 0,\ exam,\ A > 0$; and (5) issue not classified, issue not examined, $C = 0$. We now compute the likelihood function for each of these cases.

Case 1

The likelihood function for this case can be computed as the difference between the marginal probability that $C^* > 0$ (income component classified) and the joint probability that $C^* > 0$, $N^* > 0$, and $D^* > 0$ (income component classified and positive noncompliance detected):

$$L = \Phi\left(\beta_C{}'x_C\right) - BN\left(\frac{\beta_N{}'x_N - ln(h)}{\sigma_N}, \beta_C{}'x_C, \rho\right)\Phi\left(\frac{\beta_D{}'x_D}{\sigma_D}\right).$$

Case 2

The likelihood function for this case accounts for the possibilities that noncompliance is either fully or partially detected:

$$L = \frac{1}{\sigma_N(A+h)}\phi\left(\frac{ln(A+h) - \beta_N{}'x_N}{\sigma_N}\right)\Phi\left(\frac{\beta_C{}'x_C + \rho\left(\frac{ln(A+h)-\beta_N{}'x_N}{\sigma_N}\right)}{\sqrt{1-\rho^2}}\right)$$
$$\Phi\left(\frac{\beta_D{}'x_D - 1}{\sigma_D}\right) + \int_0^1\left[\frac{1}{\sigma_N\sigma_D(A+hD)}\phi\left(\frac{ln(A/D+h) - \beta_N{}'x_N}{\sigma_N}\right)\right.$$
$$\left.\Phi\left(\frac{\beta_C{}'x_C + \rho\left(\frac{ln(A/D+h)-\beta_N{}'x_N}{\sigma_N}\right)}{\sqrt{1-\rho^2}}\right)\phi\left(\frac{D - \beta_D{}'x_D}{\sigma_D}\right)\right]dD.$$

As noted above, when a income component is not classified for examination, we assume that the examiner examines the income component anyway with a probability that depends on the true level of noncompliance N:

$$\frac{exp\{\alpha_0 + \alpha_1 N\}}{1 + exp\{\alpha_0 + \alpha_1 N\}}.$$

Case 3

In this case, the income component has not been classified, but the examiner elects to review it and does not detect any noncompliance. The likelihood function for this case is computed as the sum of two joint probabilities. The first is that the income component is not classified, that it is examined, and that it is noncompliant, but that the noncompliance went undetected. The second joint probability is that the income component is not classified, that it is examined, and that it is perfectly compliant.

$$
\begin{aligned}
L = \Phi\left(\frac{-\beta'_D x_D}{\sigma_D}\right) \int_0^\infty \Bigg[& \frac{1}{\sigma_N(N+h)}\phi\left(\frac{ln(N+h)-\beta'_N x_N}{\sigma_N}\right) \\
& \Phi\left(\frac{-\beta'_C x_C - \rho\left(\frac{ln(N+h)-\beta'_N x_N}{\sigma_N}\right)}{\sqrt{1-\rho^2}}\right) \frac{exp\{\alpha_0+\alpha_1 N\}}{1+exp\{\alpha_0+\alpha_1 N\}}\Bigg] dN \\
& + BN\left(\frac{ln(d)-\beta'_N x_N}{\sigma_N}, -\beta'_C x_C, \rho\right)\left(\frac{exp\{\alpha_0\}}{1+exp\{\alpha_0\}}\right).
\end{aligned}
$$

Case 4

As with Case 3, we observe this case only when the income component is not assigned by the classifier, but the examiner elects to review the item in any case. In this case, however, the review of the income component uncovers some noncompliance. The likelihood expression is somewhat similar to that given earlier for Case 2, which involves detected noncompliance for a classified return:

$$
\begin{aligned}
L = {} & \frac{1}{\sigma_N(A+h)}\phi\left(\frac{ln(A+h)-\beta_N{}'x_N}{\sigma_N}\right)\Phi\left(\frac{-\beta_C{}'x_C-\rho\left(\frac{ln(A+h)-\beta_N{}'x_N}{\sigma_N}\right)}{\sqrt{1-\rho^2}}\right) \\
& \Phi\left(\frac{\beta_D{}'x_D-1}{\sigma_D}\right)\left(\frac{exp\{\alpha_0+\alpha_1 A\}}{1+exp\{\alpha_0+\alpha_1 A\}}\right) \\
& + \int_0^1 \Bigg[\frac{1}{\sigma_N\sigma_D(A+hD)}\phi\left(\frac{ln(A/D+h)-\beta_N{}'x_N}{\sigma_N}\right) \\
& \Phi\left(\frac{-\beta_C{}'x_C-\rho\left(\frac{ln(A/D+h)-\beta_N{}'x_N}{\sigma_N}\right)}{\sqrt{1-\rho^2}}\right)\phi\left(\frac{D-\beta_D{}'x_D}{\sigma_D}\right) \\
& \left(\frac{exp\{\alpha_0+\alpha_1(A/D)\}}{1+exp\{\alpha_0+\alpha_1(A/D)\}}\right)\Bigg] dD.
\end{aligned}
$$

Case 5

In this case, the income component is not classified, and the examiner elects not to examine the return. The likelihood expression for this case takes the form:

$$L = \int_0^\infty \left[\frac{1}{\sigma_N (N+h)} \phi \left(\frac{ln(N+h) - \beta_N' x_N}{\sigma_N} \right) \Phi \left(\frac{-\beta_C' x_C - \rho \left(\frac{ln(N+h) - \beta_N' x_N}{\sigma_N} \right)}{\sqrt{1-\rho^2}} \right) \right.$$
$$\left. \left(\frac{1}{1 + exp\{\alpha_0 + \alpha_1 N\}} \right) \right] dN + BN \left(\frac{ln(d) - \beta_N' x_N}{\sigma_N}, -\beta_C' x_C, \rho \right) \left(\frac{1}{1 + exp\{\alpha_0\}} \right).$$

Model 2: Noncompliance and Detection

For many of the income components in our analysis, an examination of the component usually takes place whenever a return has reported a nonzero amount for the component. For such income components, we have worked with a simpler model that ignores the decision whether to classify the component for examination. In this model, we focus exclusively on whether noncompliance is present and the extent to which the examiner has been successful in detecting it.

There is a further issue for these types of income components. In particular, while most returns that report a nonzero amount of the component are subject to detailed examination of that component, in most cases for returns that report a zero amount for the component the component is not examined, at least not with the same intensity. Our model therefore employs separate specifications for returns that do and do not report a nonzero amount for each income component.

For returns that report a nonzero amount for an income component, the specification has two equations:

$$\begin{aligned} ln(N^* + h) &= \beta_N{}' x_N + \epsilon_N \\ D^* &= \beta_D{}' x_D + \epsilon_D \end{aligned}, \tag{8}$$

where the observed level of noncompliance N is related to the latent variable N^* as follows:

$$N = \begin{cases} N^* & N^* > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

Similarly, the observed detection rate D is related to the latent variable D^* according to:

$$D = \begin{cases} 1 & D^* \geq 1 \text{ (complete detection)} \\ D^* & 0 < D^* < 1 \text{ (partial detection)} \\ 0 & D^* \leq 0 \text{ (nondetection).} \end{cases} \tag{10}$$

The two parts of this specification are identical with the corresponding parts for model 1; in particular the specification for noncompliance N^* and N are identical to equations (1) and (2), and the specification of the detection process is identical to equations (6) and (7). We maintain the assumptions that ϵ_N is normally distributed with mean zero and standard deviation σ_N; ϵ_D is normally distributed with mean zero and standard deviation σ_D; and that ϵ_N and ϵ_D are independently distributed.

As before, we work out the likelihood function in terms of assessed noncompliance, $A = N * D$. The likelihood function has two separate cases: $A = 0$ and $A > 0$. We consider each of these cases in turn.

<u>Case 1: $A = 0$</u>

In this case, either the taxpayer is compliant or is noncompliant but no noncompliance is detected. The likelihood function may be computed as one minus the probability that noncompliance is present and is at least partially detected:

$$L = 1 - \Phi\left(\frac{{\beta_N}' x_N - ln(h)}{\sigma_N}\right) \Phi\left(\frac{{\beta_D}' x_D}{\sigma_D}\right),$$

where $\Phi(z)$ represents the standard normal c.d.f. evaluated at z.

<u>Case 2: $A > 0$</u>

In this case, the taxpayer is noncompliant and the noncompliance is either fully or partially detected. Therefore, the likelihood function allows for detection rates ranging from zero to one:

$$L = \frac{1}{\sigma_N(A+h)}\,\phi\left(\frac{ln(A+h) - {\beta_N}' x_N}{\sigma_N}\right) \Phi\left(\frac{{\beta_D}' x_D - 1}{\sigma_D}\right) + \int_0^1 \frac{1}{\sigma_N \sigma_D (A + hD)}\,\phi\left(\frac{D - {\beta_D}' x_D}{\sigma_D}\right) \phi\left(\frac{ln(A/D + h) - {\beta_N}' x_N}{\sigma_N}\right) dD,$$

where $\phi(z)$ represents the standard normal p.d.f. evaluated at z.

For returns that report a zero amount for the relevant income component, our specification separately addresses the likelihood that the income component is in fact present and the magnitude of that component conditional on it being present. Our specification allows for detection errors both with respect to identifying whether the income component is present and with respect to assessing its magnitude when present.

We develop a specification for the joint likelihood that the income component is present and the chance that it will be detected if present:

$$P^* = {\beta_P}' x_P + \epsilon_P \tag{11}$$

$$D_P^* = {\beta_{DP}}' x_{DP} + \epsilon_{DP}, \tag{12}$$

where P^* is a latent variable describing the likelihood that some of the income component is present and D_P^* is a latent variable describing the propensity of the examiner to detect its presence.

Unreported income is present if and only if $P^* > 0$. Likewise, this income is detected if and only if $D_P^* > 0$. We assume that ϵ_P and ϵ_{DP} are each normally distributed with zero means and unit standard deviations. For convenience, we also assume that they are independently distributed.

The likelihood function for this portion of our model depends on whether the examiner has assessed that some of the income component is present.

Case 1: Examiner assesses that income component is present

In order for the examiner to assess that at least some of the income component is in fact present, it must be the case that both $P^* > 0$ and $D_P^* > 0$. Therefore, the likelihood function for this case is specified as:

$$L = \Phi(\beta_P' x_P)\Phi(\beta_{DP}' x_{DP}).$$

Case 2: Examiner assesses that income component is not present

If the examiner has assessed that the income component is not present, either $P^* < 0$ (component really is not present) or $D_P * < 0$ (detection error). The likelihood of this can be expressed as one minus the probability that $P^* > 0$ and $D_P^* > 0$:[6]

$$L = 1 - \Phi(\beta_P' x_P)\Phi(\beta_{DP}' x_{DP}).$$

[6] To ensure identification of this portion of our model, it is desirable that x_P includes at least one continuous variable that is excluded from x_{DP}

So far, our model accounts for whether the income component is assessed to be present, but it does not account for the magnitude of the adjustment when the component is deemed to be present. For returns with a positive adjustment for the income component, we assume that the magnitude of the adjustment depends on both the actual amount of the income component that is present and the extent to which it has been detected. More specifically, our specification includes the following two equations:

$$ln(N) = {\beta_N}' x_N + \epsilon_N \tag{13}$$

$$D^* = {\beta_D}' x_D + \epsilon_D, \tag{14}$$

where N represents the true magnitude of noncompliance (i.e., the magnitude of the income component that is present but which has been reported as zero), and D^* represents a latent variable for the propensity for noncompliance to be detected. We assume that ϵ_N is normally distributed with mean zero and standard deviation σ_N. Likewise, we assume that ϵ_D is normally distributed with mean zero and standard deviation σ_D.

Since this portion of model is estimated over returns that are assessed to have at least some of the income component, it must be the case that detection is either partial or complete. The distribution of D^* is therefore truncated to lie above zero. The detection rate D is defined as:

$$D = \begin{cases} 1 & D^* \geq 1 \text{ (complete detection); or} \\ D^* & 0 < D^* < 1 \text{ (partial detection).} \end{cases} \tag{15}$$

Unfortunately, there are relatively few examiners who have audited a sufficiently large number of returns (15 or more) that reported a zero amount of an income component of interest and were found to have a nonzero value for the component. In our analysis, we therefore apply the estimated parameters of the detection equation from our analysis of returns that reported a positive amount for the component. In effect, we are assuming that, once an examiner finds that the income component is present on a return that reports none of the component, his ability to detect the magnitude of noncompliance on that return is comparable to his ability to uncover noncompliance on a return that reports a nonzero amount for the income component.

As in our previous models, the observed assessed level of noncompliance is $A =$

$D * N$. The likelihood function is:

$$L = \frac{1}{\Phi(\beta_D x_D)} \left[\frac{1}{\sigma_N A} \, \phi \left(\frac{ln(A) - {\beta_N}' x_N}{\sigma_N} \right) \Phi \left(\frac{{\beta_D}' x_D - 1}{\sigma_D} \right) \right.$$
$$\left. + \int_0^1 \frac{1}{\sigma_N \sigma_D A} \, \phi \left(\frac{D - {\beta_D}' x_D}{\sigma_D} \right) \phi \left(\frac{ln(A/D) - {\beta_N}' x_N}{\sigma_N} \right) dD \right],$$

V. Empirical Results

In this section we present some data statistics and some of the results from our analysis. As noted in the introduction to this paper, due to issues of confidentiality and the need of the IRS to fully review our results before making them publicly available, we are unable to report all of our results in this paper.

Tables 1 and 2 present statistics for income components estimated using model 1, which applies to components subject to substantial third party information reporting. We estimate model 1 for the following components:

(1) Wages.
(2) Taxable interest.
(3) Taxable state and local tax refunds.
(4) Dividends.
(5) Taxable pensions and IRA distributions.
(6) Gross social security benefits.
(7) Unemployment insurance.[5]

Table 1 presents information about the number of returns in our sample reporting nonzero amounts for each of these items, and the number reporting zero. The raw number of returns, rather than the population-weighted numbers are provided to give the reader a sense of the sample sizes that are available for estimation for each income component. As expected the majority of households report some wages; the majority also report some interest. Significant numbers report nonzero amounts for each of the other items. The table also presents the percentage of returns reporting nonzero amounts for which the item is classified for examination, and the percentage of returns reporting zero for which

[5] There were too few cases involving alimony receipts to include in the analysis.

the item is classified for examination. These percentages have been weighted to give the reader a sense of the population characteristics. The majority of returns are not classified for examination of a given income component. However, a modest percentage of returns reporting nonzero amounts for a given component are classified, the highest percentages being for interest, dividends, and social security benefits. For zero amounts the percentage classified for exam in small; the one exception is interest, for which a nontrivial percentage of returns reporting zero are classified for examination. The last two columns of the table show the number of returns examined for the specified item, both returns that were classified for examination and then examined and also returns that were not classified for examination but were examined anyway. While most examinations are for returns classified for exam, a not insignificant number of returns are examined for an item which was not classified.

Table 2 presents information about adjustments for noncompliance made during examinations for these same items. These numbers are weighted to reflect the filing population. The most striking feature of the table is the cells for which the percentage of cases having a positive adjustment is high. These include certain cells for items for which the household reported zero but the classifier classified the item for examination – notably wages, interest, dividends, state and local tax refunds, and unemployment benefits. They also include certain cells for items that were not classified for examination but were examined anyway – notably interest, dividends, and state and local tax refunds. In the first group of cases the classifier presumably encountered a signal suggesting that there might be income present, and in the second group the examiner presumably encountered such a signal, even though the classifier had not. It is also interesting to note that for other items these signals are apparently less definitive – the adjustment rates are modest, for example, for social security benefits in cases in which the household reported zero and the classifier classified the item for examination and cases in which this item was not classified for examination but the examiner examined it. Assessment rates for items classified for examination are reasonable but not extraordinarily high, suggesting the classifiers use a fairly low threshold in triggering the decision to classify an item for examination.

Tables 3 and 4 present statistics for income components estimated using model 2. We estimate model 2 for the following issues/schedules:

(1) Net nonfarm sole proprietor income (Schedule C).

(2) Net farm sole proprietor income (Schedule F).

(3) Short-term capital gains.
(4) Long-term capital gains.
(5) Net rental and royalty income.
(6) Net partnership and S-corporation income.
(7) Other Schedule E income (such as estate and trust income).
(8) Supplemental gains reported on Form 4767.
(9) Other Form 1040 income.

Among the nine income components estimated based on this model, only two (net farm and nonfarm sole proprietor income) have a reasonable number of examiners who each audited that component on a sufficiently large number of returns (15 or more) to derive adequate estimates of the variation in detection rates across examiners. For the remaining seven components, we therefore estimated our model for each component jointly, restricting the parameters of the detection equation (with the exception of the constant term) to be common across all components.

Table 3 presents results for items (3)-(9) of the list, which are generally subject to some third party information reporting. Columns 1 and 3 show the number of returns that report each of these components, and the number that do not. We again note that these numbers are raw numbers from the NRP and are not weighted to reflect the U.S. filer population. As such, they provide the reader a sense of the sample sizes we have to work with for the various income components. The table also shows for each item the percentage of returns among those that report the item for which there is a positive adjustment during the NRP examination process, and the percentage of returns among those that do not report the item for which there is a positive adjustment during the NRP examination process. These percentages have been weighted to reflect the U.S. filer population. As expected, a higher percentage of returns reporting the item have a positive adjustment than of returns not reporting the item. The highest adjustment rate is for households reporting rents and royalties income.

Table 4 presents similar information for Schedule C and Schedule F. Here we find that the percentage of returns reporting these items for which there is a positive adjustment during the NRP examination process is rather high, while the percentage of returns not reporting the items for which there is a positive adjustment is quite small.

We note that these tables do not present any information about the magnitude of noncompliance, only the rate. We cannot at present provide information about magnitudes, but hopefully some of this information will be presented in subsequent work.

Tables 5 and 6 present some preliminary estimates of the distribution of classification and detection rates across classifiers and examiners in the NRP based on our econometric results. In our analysis we have restricted estimates of classifier and examiner dummies to classifiers and examiners who are assigned at least 15 cases.

Figures 1-3 present histograms based on our preliminary estimates of detection rates across examiners for three representative income items: wages, net rents and royalties, and Schedule C net income. For wages, we report results for all returns for which wages were examined, regardless of whether the taxpayer reported a nonzero or zero amount of wages on his return. In the cases of the latter two income components, we report results only for taxpayers who reported a nonzero amount of the component, for which examinations tended to be more thorough. Here we find evidence of considerably more heterogeneity than in the case of classification rates. In particular, in each category there is a subset of examiners who are estimated as "near-perfect" detectors – meaning the econometric estimation assigns them a detection rate of approximately 1.0. Essentially, these examiners serve as the benchmark against which the other examiners' detection rates are calibrated. This subset is relatively largest for wages, for which it is 36%. It is lowest for Schedule C, for which it is just 5%. For all three items the remaining examiners fall along a distribution, and possess significantly lower detection rates. There is least heterogeneity for wages. For both rents and royalties and Schedule C there is substantial heterogeneity, with the majority of examiners estimated as having detection rates below 50% (relative again to the examiners estimated as near-perfect), and a substantial number below 30%. These results are similar to previous findings for our earlier analysis at a more aggregate level, but slightly more extreme. It would be important to explore whether the examiners estimated as perfect are more experienced, and also to check on the allocation of cases across examiners, as this might partly explain the substantial differences in detection rates.

In contrast to our results for examiner detection rates, we have found much less variation in the rate at which a given line item is classified for examination. To some extent, this may reflect common guidelines followed by classifiers for some classification decisions. However, the results might also reflect the fact that the classifiers were generally quite experienced, and therefore may have had similar work patterns.

VI. Conclusion

In this paper we have presented models of taxpayer reporting and the IRS classification and examination process for the NRP, and presented preliminary results from estimation of these models. Our models focus on individual income components, the first time such a detailed level of analysis has been developed for the class of models we use.

Overall, we find that we are able to estimate the models successfully, and our estimates are broadly comparable to those obtained in previous analyses, generally using more aggregated data. In particular, our estimates of noncompliance (not presented in this preliminary paper) are broadly consistent with those found in many earlier studies. Our estimates of detection rates are also similar, but show a quite large amount of heterogeneity across examiners in detection rates for certain income items. We view the results shown here as preliminary and requiring further exploration.

References

Alexander, Craig and Jonathan Feinstein. “A Microeconometric Analysis of Income Tax Evasion and Its Detection.” Mimeo, MIT, 1987.

Alm, James, Brian Erard, and Jonathan S. Feinstein. “The Relationship between State and Federal Tax Audits,” in *Empirical Foundations of Household Taxation*, edited by Martin Feldstein and James M. Poterba, University of Chicago Press, 1996, pages 235-273.

Brown, Robert E. and Mark J. Mazur. “IRS’s Comprehensive Approach to Compliance Measurement,” mimeo, Internal Revenue Service, 2003.

Erard, Brian. “Taxation with representation : An analysis of the role of tax practitioners in tax compliance,” *Journal of Public Economics*, Volume 52, 1993, pages 163-97.

Feinstein, Jonathan S. “Detection Controlled Estimation,” *Journal of Law & Economics*, Volume 33, 1990, pages 233-276.

Feinstein, Jonathan S. “An econometric analysis of income tax evasion and its detection,” *RAND Journal of Economics*, Volume 22, 1991, pages 14-35.

Feintein, J.S. “The Safety Regulation of U.S. Nuclear Power Plants: Violations, Inspections, and Abnormal Occurrences,” *Journal of Political Economy*, Volume 109, 1989, pages 360-369.

National Research Program. *Program Prospectus.* Internal Revenue Service. 2001.

National Research Program. Individual Selection Summary Report. February 2003.

Note: All tables and figures refer exclusively to returns subject to face-to-face examinations

Table 1: Weighted Classification Rates by Whether Nonzero Amount Reported, Group 1 Income Components

Income Component	**Returns with a Nonzero Report for Income Component**		**Returns with a Zero Report for Income Component**		**Raw # Total Examined Returns**	
	Raw # returns	**Weighted % that Were Classified**	**Raw # returns**	**Weighted % that Were Classified**	**Classified**	**Not Classified, but Examined**
Wages	26,418	12.1	11,452	1.8	2,507	934
Interest	27,937	27.6	9,933	16.3	11,123	688
Dividends	16,692	33.2	21,178	4.5	6,875	397
State & local tax refunds	10,190	11.8	27,680	5.4	2,738	198
Pensions and IRAs	8,076	21.1	29,794	5.4	2,850	217
Gross social sec benefits	3,989	36.5	33,881	1.3	1,952	181
Unemployment benefits	1,692	9.6	36,178	0.97	272	30

Table 2: Weighted Percentage of Examined Returns with a Positive Adjustment by Classification and Reporting Status, Group 1 Income Components

Income Component	**Income Component Classified**		**Income Component Not Classified, but Examined Anyhow**
	Nonzero report for income component	**Zero report for income component**	
Wages	33.3	73.7	24.5
Interest	26.8	92.9	68.0
Dividends	27.3	82.5	67.9
State & local tax refunds	25.0	66.8	65.9
Pensions and IRAs	19.5	48.3	33.8
Gross social sec benefits	13.5	14.3	16.9
Unemployment benefits	17.9	82.6	44.9

Note: Wages variable excludes tip income.

Table 3: Reporting and Examiner Adjustment Statistics, Group 2 Income Components

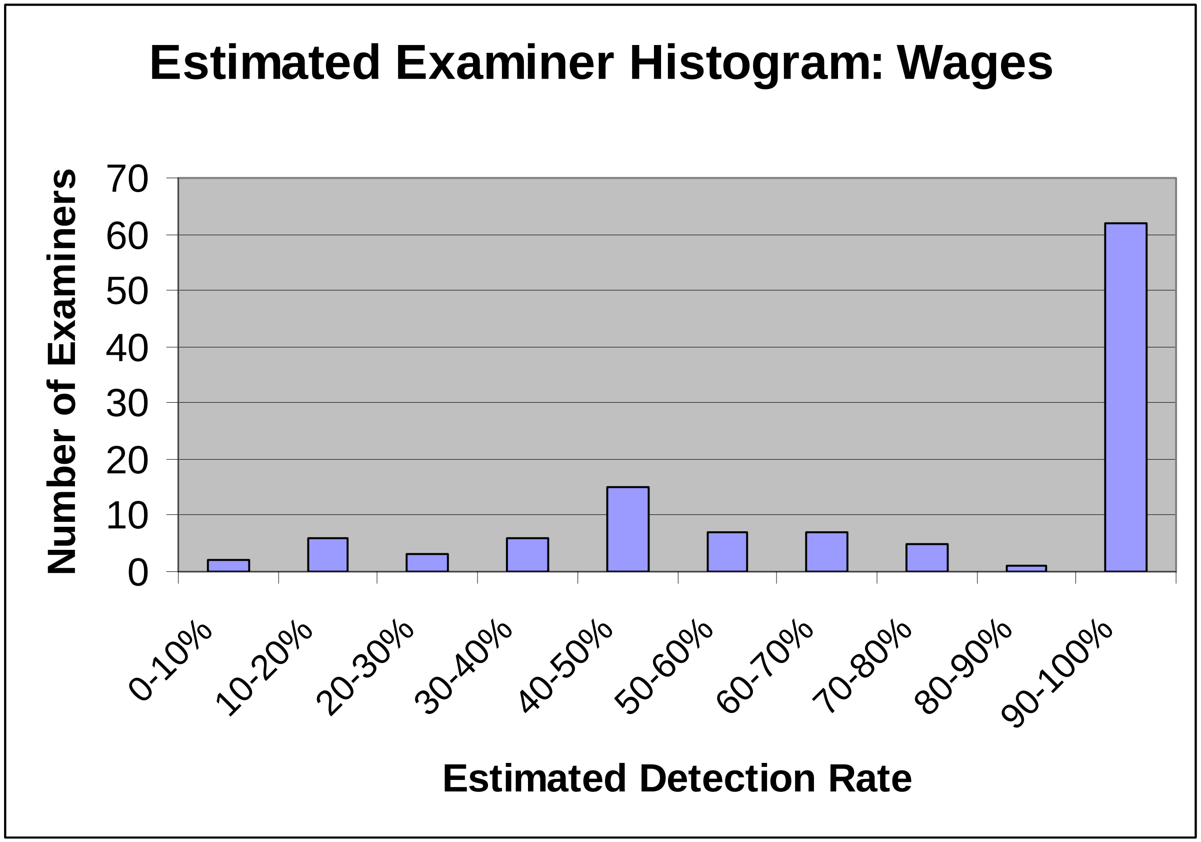
Income Component	**Income Component Reported**		**Income Component Not Reported**	
	Raw # returns	**Weighted % of returns with a positive adjustment**	**Raw # returns**	**Weighted % of returns with a positive adjustment**
Sched. D short term gains	7,981	11.1	29,889	1.3
Sched. D long term gains	13,571	14.7	24,299	2.8
Net rents and royalties	7,400	43.1	30,470	0.54
Net income from partnerships and S-corps	6,339	13.2	31,531	0.11
Other Sched. E income	1,004	14.6	36,866	0.03
Form 4797 gains	2,945	16.8	34,925	0.25
Other income	4,848	10.1	33,022	3.3

Table 4: Reporting and Examiner Adjustment Statistics, Group 3 Income Components

Type of Sole Proprietor Schedule	**Schedule Filed**		**No Schedule Filed**	
	Raw # schedules	**Weighted % of schedules with a positive adjustment**	**Raw # returns**	**Weighted % of returns with a positive adjustment**
Non-farm (Schedule C)	23,943	55.4	17,557	1.7
Farm (Schedule F)	4,830	56.5	33,204	0.01

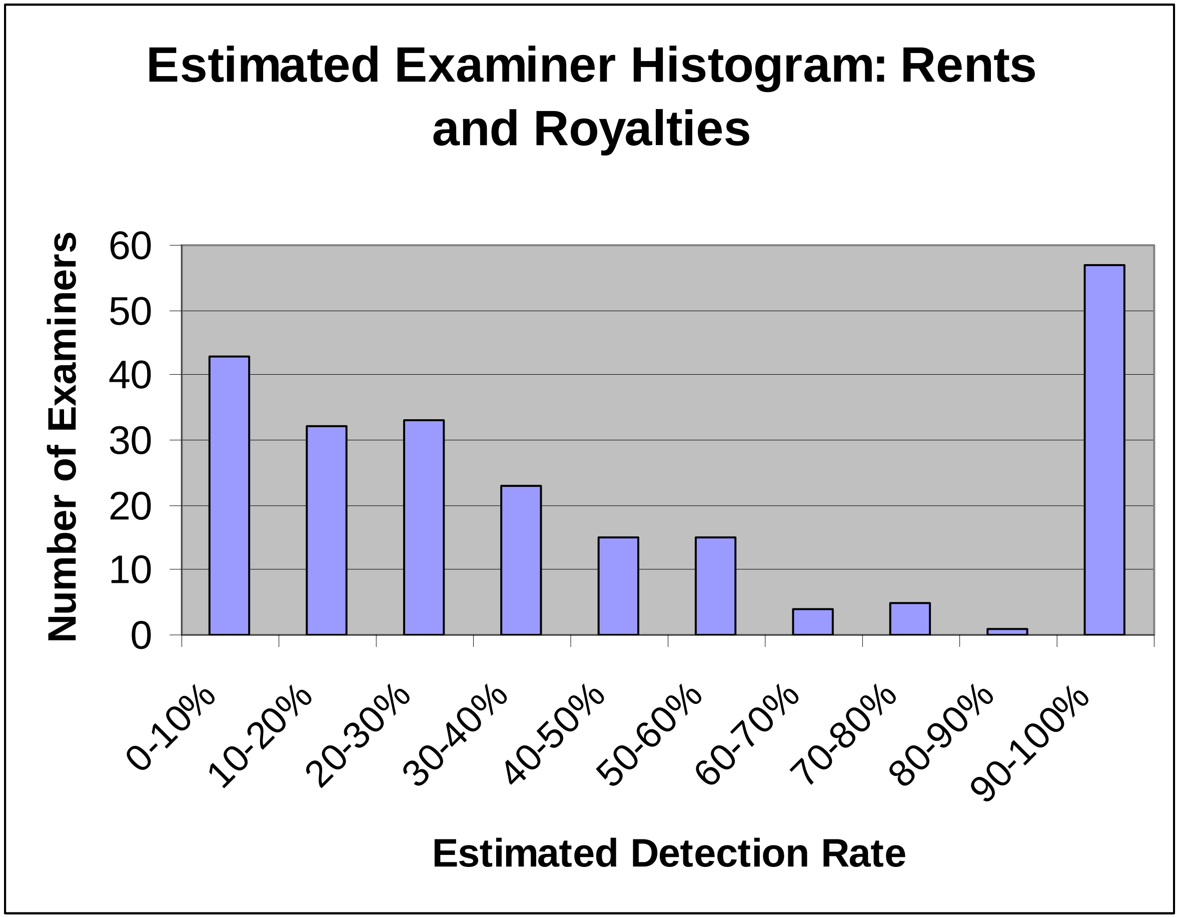
Note: Some taxpayers file multiple Schedule C or Schedule F returns; each schedule is counted separately in our statistics and our econometric analysis.

Figure 1



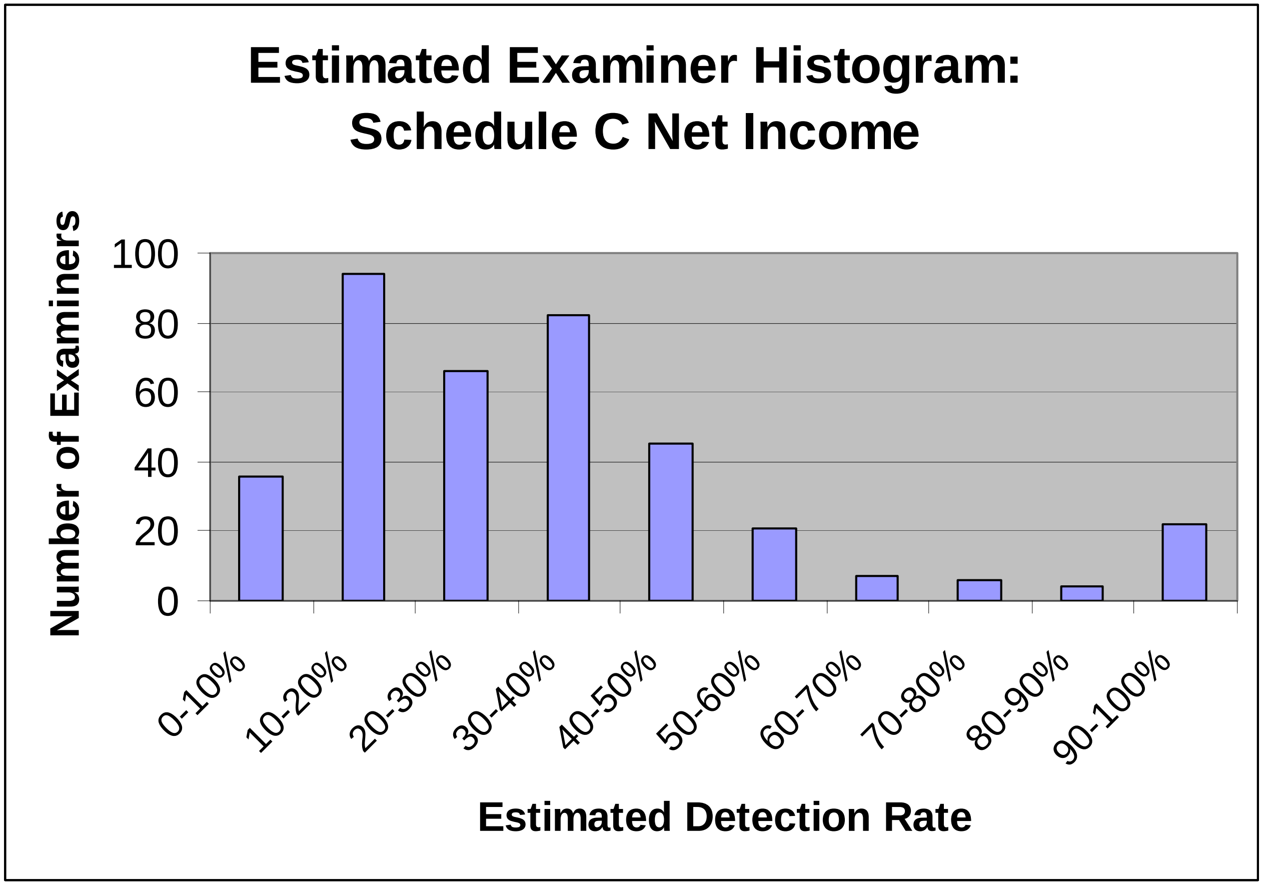
Average Detection Rate for All Examiners: 88%

Figure 2



Average Detection Rate for All Examiners: 47%

Figure 3



Average Detection Rate for All Examiners: 32%