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Abstract

Much of the tax compliance literature focuses on taxpayers who choose to underreport their income when they file their tax returns. In this paper, we instead concentrate on those individuals who take the ultimate compliance shortcut of not filing a return at all – a group commonly referred to as "ghosts" by academics, tax administrators, and policy-makers. To learn more about this relatively understudied population, we undertake a detailed analysis of administrative data and Census survey data spanning the period from 2001 through 2013. Our results indicate that 10-12 percent of taxpayers with a US federal filing requirement fail to submit a timely income tax return in any given year, and 6.5-8 percent never file at all. The federal tax gap associated with these ghosts is substantial, amounting to an estimated $37 billion per year. We employ a novel pooled time-series cross-sectional econometric methodology to examine the drivers of late filing and nonfiling behavior. The results establish that filing compliance is influenced by income visibility as well as financial incentives, such as refundable credits, tax rebates, and the monetized filing burden. In addition, we find strong evidence of socio-economic and demographic influences. Our results also reveal substantial persistence in filing behavior. The estimated likelihood of filing a timely return for the current tax year is estimated to be 45 percentage points higher if the taxpayer filed a return for the preceding year. At the same time, we find that one-time financial incentives have only a temporary impact on filing compliance, overturning the prevailing view that, once an individual is brought into the tax system, that individual will continue to file in subsequent years.

Keywords: Tax Compliance, Tax Evasion, Nonfilers, Ghosts, Income Tax, Qualitative Response Models, Discrete Choice Analysis

JEL Codes: H24, H26, H31, C35

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1. Introduction

Beginning with the seminal work of Allingham and Sandmo (1972) and continuing to the present day, the main focus of the academic literature on tax compliance has been on the reporting decision faced by filers of tax returns. In fact, however, a fairly substantial number of individuals never advance to this stage of the tax compliance process but instead follow the alternative path of not filing a return at all. These "ghosts" (as they are commonly referred to by academics, tax administrators, and policy-makers) not only lurk outside most theoretical models of tax compliance, they are also absent from the taxpayer rolls, which makes it challenging to account for their presence in empirical studies of tax evasion.[1]

In this paper, we undertake an exploration of ghosts in the US federal individual income tax machinery. As a starting point, we present in Section 2 estimates of the overall size and trend of the ghost population. This is followed in Section 3 by a detailed assessment of how nonfilers impact tax revenue. Section 4 explores the economic incentives to become a ghost, and Section 5 introduces a novel econometric methodology for evaluating how these incentives drive real world taxpayer filing decisions based on pooled samples of administrative and Census data covering the period from 2001 through 2013. The data used in our analysis is described in Section 6, and the results of our econometric analysis are presented in Section 7. Some concluding remarks are offered in Section 8.

2. Voluntary Filing Rate

In the US, taxpayers generally are not required to file a federal individual income tax return if their gross income is below a specified filing threshold, although many do so to claim refunds or take advantage of refundable tax credits.[2] In such cases, choosing not to file is purely a matter of choice and has no legal ramifications. Consequently, we restrict our focus in this study to the filing behavior of taxpayers with a legal filing obligation.

The IRS defines the Voluntary Filing Rate (VFR) as the percentage of taxpayers with a legal filing obligation who file a timely federal individual income tax return. In this section, we present estimates of the VFR over the period from tax year 2001 through 2013. Our estimates are based on the methodology described in Langetieg, Payne, and Plumley (2017). Under this approach, the VFR is estimated by dividing an estimate of the number of timely filed required individual income tax returns by an estimate of the total number of required returns.

The numerator of this expression is determined by counting the overall number of required returns for a given tax year that were filed by the relevant deadline (accounting for all valid extensions). Required returns within the timely filing population are identified using a computer algorithm that applies the legally established filing criteria for that year. For most filers, this involves an assessment of whether the reported level of gross income exceeds the applicable filing threshold based on the taxpayer's filing status, whether the taxpayer is age 65 or older, and whether the taxpayer is a dependent. In the case of filers with self-employment income, the algorithm also assigns a required-return status if net self-employment income is $433 or greater.[3]

The denominator of the VFR formula expands the count in the numerator to include required returns that were filed after the deadline as well as those that were never filed. A count of late-filed required returns is based on a tally of all required individual income tax returns that were submitted to the IRS after the filing deadline. The same computer algorithm that was applied to evaluate whether a timely return was required has been applied to identify late-filed returns with a legal filing obligation.

To estimate the number of required returns that were never filed, we begin by identifying the population of individuals who are listed on third-party information documents for the year in question, such as W-2 and 1099 forms, but who are not listed as a primary or secondary filer on a federal individual income tax return for that year.[4] These information returns provide us with details on various sources and levels of income that contribute to gross income. Since self-employment earnings are generally not subject to third-party reporting, an imputation process is used to assign self-employment income to selected members of this population.[5] Taxpayers who are of age 65 or older are subject to a different filing threshold than younger taxpayers. To account for this difference, we link all members of the nonfiler population that we have been able to identify to Social Security Masterfile (DM-1) records, which contain the requisite age information. The applicable filing threshold also depends on the taxpayer's filing status and dependency status. An imputation procedure is employed to match spouses, designate filing statuses, and assign dependents using DM-1 information on age and gender.[6] Finally, a computer algorithm is applied to identify and count how many members of our identified population of nonfilers appear to have had a legal filing obligation based on the applicable filing threshold and the presence or absence of self-employment earnings.

Figure 1 displays the estimated trend in the VFR over the period from tax year 2001 through tax year 2013. As shown in the figure, the VFR estimates fluctuate modestly over this period, ranging from 88.1 to 90.5 percent.

Table 1 provides a more detailed breakdown of these estimates. Among those who fail to file a required return on time for any given tax year, roughly three-fifths never file at all. Furthermore, among those who do file a late return, roughly 20 percent do so only after receiving a notification from the IRS reminding them of the requirement to file a return.

3. Impact of Nonfiling on Tax Revenue

When assessing the tax revenue implications of nonfiling, it is important to recognize that many nonfilers have made tax prepayments in the form of employer withholding or estimated tax payments. In addition, some are eligible for refundable tax credits that would reduce their balance due or even entitle them to a tax refund. It is therefore essential to account for such prepayments and credits when assessing whether a given nonfiler has an outstanding tax liability.

The IRS defines the nonfiling tax gap as the aggregate tax balance that is owed by nonfilers with a positive balance due as of the filing deadline. Estimation of the nonfiling tax gap relies largely on the same information that was employed under our VFR estimation methodology to evaluate the number of required individual income tax returns that were not filed by the deadline.[7] For late filers, the starting point for tax gap estimation is the return that was ultimately filed. The income amounts reported on the return are adjusted to account for any apparent omissions that are revealed through a comparison with matched third-party information documents. A computer algorithm is then employed to check whether the taxpayer had a legal filing obligation based on the applicable filing threshold and the presence or absence of self-employment earnings. If so, a tax calculator is applied to assess total tax liability. Tax prepayments and credits are then subtracted from this figure to determine the tax balance that was outstanding as of the filing deadline. The portion of the nonfiling tax gap attributable to late filers is then computed by aggregating the outstanding tax balances across all late filers with a positive balance due.

In the case of individuals who never filed a required return, the starting point for the tax gap estimates is the aforementioned estimates of the sources and levels of income and imputations of filing status and dependency status derived from matched third-party and administrative data sources.[8] To arrive at the tax base, an imputation process is employed to account for exemptions and deductions from the estimated income amounts. A tax calculator is then applied to compute tax liability net of imputed tax credits. Tax prepayments are then subtracted to obtain an estimate of the outstanding tax balance.

Table 2 presents estimates of the average nonfiling tax gap for the federal individual income tax over tax years 2011 through 2013. Over this period, the average estimated gap inclusive of self-employment taxes amounted to $37.4 billion per year. Of this total, approximately $12.1 billion was owed by individuals who eventually filed a late return, sometimes after receiving an IRS enforcement contact. These late filers ultimately reported and paid much of their outstanding liability. On the other hand, the portion of the tax gap attributable to individuals who never filed ($25.3 billion) can be expected to remain largely unpaid.[9]

As indicated in Table 3, the nonfiling tax gap is highly concentrated with 63.7 percent of the overall gap attributable to the top balance due decile in tax year 2010.

The nonfiling tax gap estimates that are presented in Table 2 are based on taxpayers who have a positive tax balance remaining after accounting for prepayments and refundable credits. However, many taxpayers who fail to file a timely required return are actually due a refund. Indeed, late filers as a whole were entitled to an estimated aggregate refund of $6.4 billion for tax year 2010. In contrast, those who never filed their required tax year 2010 return (including both nonfilers with a balance due and nonfilers entitled to a refund) had an aggregate estimated tax balance for that year of $13.8 billion.[10] Overall, then, the federal tax revenue savings associated with nonfilers who fail to claim refunds to which they are entitled only partially offsets the losses attributable to nonfilers who fail to pay their positive tax balances.

4. Theoretical Insights

Under the standard economic model of tax compliance, the filing of a tax return is a foregone conclusion. The question is not *whether* the taxpayer will make a report, but rather *how much* will he or she choose to report. Under this framework, the taxpayer approaches the tax reporting decision as he or she would an ordinary gamble, balancing the prospect of retaining a greater income share under successful tax evasion against the risk of audit and penalty. In particular, the taxpayer chooses an amount *X* of income to report to maximize expected utility (*EU*):

$$EU = (1-p)U[Y - tX] + pU[Y - tY - \theta t(Y - X)],$$

where p is the audit risk, *t* is the tax rate (assumed here to be proportional), Y is the taxpayer's true income that should be reported, *X* is the amount actually reported on the return, θ represents the penalty rate on the unreported tax amount, and $U[z]$ represents the taxpayer's utility associated with net income *z*. In more sophisticated versions of this model, the audit probability for a given tax report might be strategically chosen by the tax authority, true income might depend on an individual's labor supply decision, the tax rate might vary with the level of income, taxpayer perceptions of risk may deviate from actual risk, audits may not identify all instances of underreporting, and various additional pecuniary and non-pecuniary factors might influence decisions. However, this simple specification captures the basic insight that taxpayers have an incentive to underreport an additional dollar of income so long as the terms of the risk-reward tradeoff are favorable for one's marginal utility.

To account for ghosts, Erard and Ho (2001) extended this framework to consider what would happen if no return were filed at all. In this extended framework, an individual separately considers his or her potential utility under scenarios where (s)he does and does not file. Under the filing scenario, the individual must choose not only how much income X to report, but also how much tax to prepay through withholding or estimated tax payments. In addition, there is a compliance cost *c* associated with filing. The expected utility under this scenario EU_F is:

$$EU_F = (1-p)U[Y - tX - \gamma(\bar{W} - W) - c] + pU[Y - tY - \theta t(Y - X) - \gamma(\bar{W} - W) - c],$$

where $\overline{W}$ is the minimum required tax prepayment amount and γ is the penalty rate on under-withholding.[11] Based on this scenario, the taxpayer would choose to make the minimum tax prepayment $\overline{W}$ if (s)he were to file. He or she would then select the value of X that maximizes the above expression, conditional on $W = \overline{W}$. At this report, the net marginal expected utility associated with reporting an additional dollar of income would be equal to zero.

Under the nonfiling scenario, the taxpayer has only to choose how much tax to prepay (W), recognizing that his or her expected utility ($EU_{\bar{F}}$) depends on the risk of enforcement and the accompanying tax and penalty assessments:

$$EU_{\bar{F}} = (1-q)U[Y-W] + qU[Y-tY-f(tY-W)-c],$$

where q is the risk of nonfiling enforcement and f is the penalty rate on the unpaid tax balance. If apprehended, the nonfiler would be required to submit a tax return, so the above expression accounts for the filing burden c in the event of nonfiler enforcement. At the optimal choice of W under this nonfiling scenario, the net expected marginal utility associated with prepaying an additional dollar of tax would be equal to zero.

To decide whether to file a return, the individual separately computes his or her maximum expected utility under the filing and nonfiling scenarios and chooses the option that produces a higher result. To understand what drives this decision, it is instructive to consider the base case where the filing burden c is equal to zero, the risks of enforcement under the two scenarios are equal ($p = q$), and the penalty rates are the same ($\theta = f$). In this case, Erard and Ho (2001) show that the maximum expected utility under the two scenarios is exactly the same, so that the individual is indifferent about whether to file a return. If the individual were to file, (s)he would make a tax prepayment of $W = \overline{W}$ and (s)he would make an optimal income report X^*. Alternatively, the individual could achieve the same expected utility by making a tax prepayment of $W = tX^*$ but not filing a return at all. Thus, the magnitude of the filing burden and the relative rates of risk and penalty are what drive filing behavior in this model. Individuals are more likely to be ghosts when the filing burden c is high, the risk of nonfiler enforcement q is low relative to the audit rate p, and the penalty rate facing nonfilers f is low relative to that faced by filers θ.[12]

5. Econometric Framework

In this section we present a novel econometric framework to empirically implement the theoretical insights from Section 4. Typically, researchers evaluate the drivers of a participation decision (such as filing a tax return) using a qualitative response model, such as probit or logit. However, the application of such a model requires detailed information on the relevant characteristics of a representative sample of both participants and non-participants. Although the IRS has very detailed information on filers of individual income tax returns, it lacks comparably detailed information on nonfilers. To address this informational gap, we supplement IRS information on the characteristics of filers with publicly available Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) data on the characteristics of both filers and nonfilers in the general population. Although this latter data source does not identify which respondents are filers and which are nonfilers, we are nonetheless able to estimate a qualitative response model using the calibrated qualitative choice estimation methodology developed by Erard (2020).

5.1 *Calibrated Probit Model*

In a recent paper (Erard *et al.*, 2020), we undertook a preliminary exploratory study of filing behavior using the calibrated qualitative choice estimation framework. In it, we performed a cross-sectional calibrated probit analysis of the likelihood of filing a tax year 2010 federal individual income tax return. As discussed in Erard (2020), the calibrated probit model is estimated by solving the following optimization problem:

$$\max_{\beta} \sum_{i=1}^{n} ln[\Phi(\beta' x_i)]$$

$$s.t. \quad \sum_{j=1}^{n_o} w_j \Phi(\beta' x_j) = N.$$

In the empirical application by Erard *et al.* (2020), *n* represents the number of filers in a random sample from the required return filing population for tax year 2010, n_o is the size of a supplementary stratified random sample containing both required filers and nonfilers from this tax year, *x* is a vector of explanatory variables, β is a vector of coefficients to be estimated, $\Phi(z)$ represents the value of the standard normal cumulative distribution function evaluated at z, *w* refers to sample weights that are used to make the supplementary sample representative of the underlying population, and *N* is the population number of required returns filed. The supplementary sample contains no information that can be used to distinguish filers from nonfilers.

The solution to the above estimation problem is the value of β that maximizes the joint predicted likelihood of filing among taxpayers in the filer-only data sample subject to the constraint that the weighted aggregate predicted number of filers in the supplementary sample is consistent with the actual number of required filers in the population. Intuitively, whereas an ordinary probit analysis would identify β through a comparison of the characteristics of individuals who filed against the characteristics of individuals who did not file, identification in this framework is achieved through a comparison against the characteristics of individuals from the general required return population (including both filers and nonfilers). Under this approach, the estimated value of β is "calibrated" to be consistent with the population count of filed required returns (hence the name "calibrated probit analysis").

5.2 *Methodological Contributions*

In this study, we build in three main ways on our earlier exploratory work to develop a deeper understanding of the drivers of nonfiling behavior. First, we generalize the calibrated qualitative choice estimation framework to accommodate a pooled time series of cross-sections so that we can understand what drives trends as well as individual differences in filing behavior. Second, we undertake a multinomial choice analysis to distinguish between those who file late and those who never file. Third, we examine persistence in filing behavior by generalizing the econometric methodology to account for prior filing history.

Pooled time series cross-sectional framework

In this section we generalize the calibrated qualitative choice estimation framework of Erard (2020) to permit its application to a time series of cross-sections. Let *t* represent the tax year ($t = 1, \dots, T$). Under the extended framework, the optimization problem takes the form:

$$\max_{\beta} \sum_{t=1}^{T} \sum_{i=1}^{n_t} ln[\Phi(\beta' x_{it})]$$

$$s.t. \begin{cases} \sum_{j=1}^{n_{o1}} w_{j1} \Phi\left(\beta' x_{j1}\right) = N_1 \\ \sum_{j=1}^{n_{o2}} w_{j2} \Phi\left(\beta' x_{j2}\right) = N_2 \\ \quad\quad\vdots \\ \sum_{j=1}^{n_{oT}} w_{jt} \Phi\left(\beta' x_{jT}\right) = N_T, \end{cases}$$

where n_t represents the number of timely required filers in the primary random sample from the overall required filing population in tax year *t*, n_{ot} is the size of the supplementary stratified random sample containing both timely required filers and nonfilers from that tax year, w_{jt} refers to sample weight associated with the j^{th} individual in the supplementary sample from tax year *t*, and N_t is the population number of timely filed required returns in that tax year. Observe that the extended framework involves T equality constraints (one for each tax year).[13]

Calibrated Multinomial Logit Model

As a second extension, we expand the estimation framework to distinguish between late filers and taxpayers who never file. Let m represent the filing outcome, where

$$m = \begin{cases} 0 \text{ (never filed)} \\ 1 \text{ (filed on time)} \\ 2 \text{ (filed late).} \end{cases}$$

Let m_{it} serve as an index for the outcome observed for taxpayer *i* in tax year t, and let $P(m_{it}|x_{it};\beta)$ represent the conditional probability of this outcome given the taxpayer's observed characteristics x_{it}. Then we can estimate the choice parameter vector β from our time series of cross-sections by solving the following constrained optimization problem:

$$\max_{\beta} \sum_{t=1}^{T} \sum_{i=1}^{n_t} ln\big(P(m_{it}|x_{it};\beta)\big)$$

$$s.t. \begin{cases} \sum_{j=1}^{n_{01}} w_{j1} P\big(m|x_{j1};\beta\big) = N_{m1} \\ \sum_{j=1}^{n_{02}} w_{j2} P\big(m|x_{j2};\beta\big) = N_{m2} \\ \vdots \\ \sum_{j=1}^{n_{0T}} w_{jT} P\big(m|x_{jT};\beta\big) = N_{mT} \end{cases}$$

for m = 1, 2,

where N_{mt} represents the aggregate number of members of the required-to-file population with outcome m in tax year t. Overall, then, this estimation problem is subject to a total of 2*T equality constraints. For estimation purposes, we assume that the conditional outcome probabilities follow the multinomial logit distribution:

$$P\left(m_{jt}\middle|x_{jt};\beta_0,\beta_1,\beta_2\right)=\frac{e^{\beta_j' x_{jt}}}{1+e^{\beta_1' x_{jt}}+e^{\beta_2' x_{jt}}},$$

where β_0 has been normalized to one.

Accounting for Prior Year Filing Behavior

Prior research by Erard and Ho (2001) indicates that the likelihood of filing for the current tax year depends on whether the taxpayer has filed for the prior year. In this section, we extend the calibrated probit methodology to account for prior-year filing behavior. The key challenge associated with this extension is that prior-year filing behavior is only partially observed. Specifically, we observe such behavior only within the primary filer-only sample; no information on either current or prior-year filing behavior is available in the supplementary CPS-ASEC sample of filers and nonfilers employed in this study.

To make the estimation problem tractable, we incorporate an additively separable prior-year filing effect in our specification of the timely filing probability. Let F_{it} be a dummy indicator for whether taxpayer *i* has filed a timely return in period *t.* Then the probability that the taxpayer has timely filed in period *t* is specified as:

$$\Pr(F_{it}{=}1)=\Phi(\beta' x_{it})+\gamma F_{i(t-1)}.$$

Our generalized calibrated probit estimator that incorporates prior-year filing behavior can then be obtained as the solution to the following constrained optimization problem:

$$\max_{\beta}\sum_{t=1}^{T}\sum_{i=1}^{n_t} ln\left[\Phi(\beta' x_{it})+\gamma F_{i(t-1)}\right]$$

$$s.t.\quad\begin{cases}\left(\sum_{j=1}^{n_{o1}} w_{j1}\Phi\left(\beta' x_{j1}\right)\right)+\gamma N_0^F=N_1\\ \left(\sum_{j=1}^{n_{o1}} w_{j1}\Phi\left(\beta' x_{j1}\right)\right)+\gamma N_1^F=N_2\\ \quad\vdots\\ \left(\sum_{j=1}^{n_{o1}} w_{j1}\Phi\left(\beta' x_{j1}\right)\right)+\gamma N_{T-1}^F=N_T,\end{cases}$$

where N_t^F represents the aggregate number of taxpayers with a legal filing obligation for tax year (t+1) who filed a return for tax year t, where $t = 0, 1, \ldots, (T-1)$. Since measures of these aggregate filing statistics are available, estimation of our model is feasible.[14] In contrast, observe that it would not be feasible to estimate our model in the absence of our additive separability assumption. In that case, one would need to know the prior-year filing status of each individual in the supplementary sample.

A potential issue with the above estimation methodology is that the predicted probability of filing in the current period can fall outside the permissible range from zero to one. To address this possibility, we employ inequality constraints in our estimation routine to ensure that all predicted filing probabilities fall within this range.[15]

6. Data Description

Our IRS data source on filers is a detailed extract of return information from all federal individual income tax returns filed for a given tax year, which has been derived from the Individual Returns Transaction File (IRTF). Many taxpayers have no legal filing obligation because their income is below the filing threshold and they do not meet certain other filing criteria, such as a need to report self-employment tax or taxes on unreported tip income. Some of these taxpayers do file, however, to claim refunds of withheld earnings or to claim a refundable tax credit, such as the Earned Income Tax Credit (EITC). Since our focus is on filing compliance, we restrict our IRTF sample to taxpayers with a legal filing obligation. This is achieved by applying a computer algorithm to check whether a given return satisfies any of the various conditions that trigger a filing requirement (such as gross income above the relevant filing threshold or net self-employment earnings in excess of $433).

Our supplementary sample of filers and nonfilers is drawn from the CPS-ASEC. In past research, we have found that certain income sources are understated in this survey. Therefore, in order to more accurately identify households with a legal filing obligation, we follow Erard *et al*. (2014) in imputing additional income across the sample (in many cases, based on third-party information return data). To assign household members to tax returns, we also impute tax filing status. The CPS-ASEC is a stratified random sample; however, the stratification criteria are not publicly available. A desirable feature of our econometric methodology is that we are able to effectively control for the stratified nature of the sample simply by applying the sample weights.[16]

For both data sources, we have large cross-sectional samples from each of tax years 2001 through 2013. The data for any given year includes a simple 0.1% random sample of between 108,000 and 119,000 required filers from the IRTF and a stratified random CPS-ASEC sample of between 53,000 and 80,000 filers and nonfilers from the general required-to-file population.

6.1 *Explanatory Variables*

Because our estimation methodology relies on a comparison of variables from two separate data sources (IRTF and CPS-ASEC), it is important to restrict the set of regressors to those variables that are comparably measured in the two sources. So, for instance, while the IRTF provides information on whether a taxpayer is owed a refund or has a balance due (which is likely to be relevant to the filing decision), comparable information is not available in the CPS-ASEC.[17] It also would be desirable to include some indicators of filing status as explanatory variables. However, a non-trivial number of taxpayers claim the incorrect status on their return. For instance, the percentage of filers claiming head of household status greatly exceeds the estimated percentage of required returns with this status based on the CPS-ASEC. Instead of relying on specific filing status indicators, we therefore include an overall indicator for marital status in our specifications, which is more reliably measured in both data sources.[18] Similarly, we would like to account for Earned Income Tax Credit eligibility in our analysis. However, a claims-based measure from the IRTF would be misleading, owing to the presence of a substantial number of EITC claimants who are not truly eligible. Ultimately, we have selected the following explanatory variables for our analysis, which we believe are measured reasonably comparably across our two data sources:

CONST: Constant term

PRIOR YEAR FILER: Dummy for having filed in the prior year (only included in the specification for the extended calibrated probit model)

AGE 65: Dummy for primary or secondary filer age 65 or over

MARRIED: Dummy for married taxpayer

CHILD3UP: Dummy variable for having 3 or more dependent children

CHILD3UP*POST2008 Interaction term that equals one when CHILD3UP is equal to one and the time period is later than tax year 2008

LN(GROSSINC): Natural log of gross income, where gross income is computed as the sum of the positive amounts of wages and salaries, interest, taxable dividends, pensions, rents, unemployment compensation, taxable social security benefits, alimony, and gross self-employment earnings

SEFILREQ: Dummy variable for a filing requirement triggered by having net earnings from farm and nonfarm self-employment in excess of $433

NEARTHRESH: Dummy variable for gross income less than 1.10 times the filing threshold, where the filing threshold for non-dependent joint filers is applied for married joint filing status and the filing threshold for single filers is applied to all other non-dependent filers. The lower statutory thresholds are applied to single and married dependent filers.

LN(BURDEN): Natural log of the real monetized taxpayer filing burden

LN(BURDEN)*NEAR THRESHOLD: Interaction between LN(BURDEN) and NEARTHESH

NO TAX STATE: Dummy variable for residence in a state with no individual income tax (AK, FL, NH, NV, SD, TN, TX, WA, WY)

MIDATL: Dummy variable for residence in the Mid-Atlantic Census division

EASTNC: Dummy variable for residence in the East North Central Census division

WESTNC: Dummy variable for residence in the West North Central Census division

SOUTHATL: Dummy variable for residence in the South Atlantic Census division

EASTSC: Dummy variable for residence in the East South Central Census division

WESTNC : Dummy variable for residence in the West South Central Census division

MOUNTAIN : Dummy variable for residence in the Mountain Census division

PACIFIC : Dummy variable for residence in the Pacific Census division

YR2002 – YR2013: Dummy variables for tax years 2002 through 2013

The omitted Census division is New England, and the omitted tax year is 2001. Beginning in tax year 2009, the Earned Income Tax Credit was expanded for families with three or more children, which created an additional incentive for such households to file a return. To capture this effect, the dummy for the presence of three or more child dependents has been interacted with a dummy for the post-implementation period.

Most taxpayers reside in jurisdictions with a state income tax filing requirement. On the one hand, such individuals may face a stronger incentive not to file if they perceive that they can avoid both state and federal income taxes by doing so. On the other hand, the failure to file a required state return may result in a higher risk that the failure to file both returns will be discovered. To account for the possibility that filing compliance at the federal level is influenced by the presence or absence of a state income tax filing requirement, a dummy variable is included for residence in one of the nine states without an income tax.[19]

Taxpayers with more than a trivial amount of net self-employment earnings are required to file a return, even when their gross income is below the filing threshold. This is because such taxpayers are subject to self-employment taxes, which are collected as part of the individual income tax filing. Since self-employment earnings are not typically captured through third-party reporting, however, such taxpayers may perceive a relatively low risk that they will be detected if they elect not to file. The self-employment filing requirement dummy is included to account for this possibility.

Taxpayers who have income close to the filing threshold may also perceive a relatively low risk associated with not filing a tax return. To account for this possibility, we have included a dummy variable for individuals with gross income that is no more than 10 percent above the filing threshold.

As discussed in Section 4, a relatively high filing burden creates a disincentive to file. We have developed estimates of the burden of filing (in real dollars) for each taxpayer in our data samples by applying prediction formulas developed from periodic IRS taxpayer burden surveys. The natural log of the estimated burden is included as a regressor in the analysis. A high filing burden may pose an especially strong disincentive to file when the risk of detection is low. For this reason, we have included an interaction term between the dummy variable for gross income near the filing threshold and our burden measure.

6.2 *Summary Statistics*

Table 4 provides separate tabulations of the thirteen-year averages of the explanatory variables from our IRTF sample of filers and our weighted CPS-ASEC sample of nonfilers (both restricted to taxpayers who have a legal filing obligation). It is important to recognize that, although the weighted CPS-ASEC sample is composed of both filers and nonfilers, the VFR hovered around 89 percent over the sample period. Since nonfilers therefore make up only a small share of the CPS-ASEC sample, a modest difference in a given statistic between the IRTF and CPS-ASEC samples is indicative of a substantial difference in this statistic between filers and nonfilers. The results show that filers were relatively more likely to be age 65 or older, live in the Mid-Atlantic or East North Central Census divisions, and, especially since tax year 2009, have three or more children. They were relatively less likely to be married, receive non-trivial self-employment earnings, or reside in the Mountain or Pacific divisions. On average, the gross income of filers was lower than that of nonfilers, and filers also faced a somewhat lower filing burden. Not surprisingly, those who filed a return for the prior tax year are relatively more likely to have filed for the current year.

7. Estimation Results

In this section we present the results of the econometric analysis of our pooled time-series cross-sectional data samples for tax years 2001-2013. Table 5 summarizes the findings for our three alternative models: (1) calibrated probit model of the likelihood of filing a timely return; (2) calibrated multinomial logit model of the likelihood of filing a timely return and the likelihood of filing a late return; and (3) calibrated probit model of the likelihood of filing a timely return, generalized to account for prior-year filing behavior. To assist with the interpretation of the findings, the estimated marginal effects and their t-statistics are included for each model. We selectively compare and contrast our findings with existing results from the studies by Plumley (1996), Erard and Ho (2001), and Erard *et al.* (2020).

7.1 *Calibrated Probit Model Findings*

The results indicate that elderly taxpayers are relatively more likely to file than younger taxpayers, a finding also reported in the aggregate state-level panel data analysis by Plumley (1996) and the micro-level audit based study by Erard and Ho (2001). All else equal, the likelihood of filing is 10.6 percentage points higher when the individual is age 65 or over. Gross income is also positively associated with filing compliance. All else equal, a filing unit with $90,000 in gross income is estimated to be about 4.3 percentage points more likely to file than a more typical filing unit with a gross income of $45,000.

Filing compliance is also linked to marital status. Compared to an unmarried individual with similar characteristics, a married individual is estimated to be about 7.2 percentage points less likely to file. In contrast, Plumley (1996) found a negative relationship between the share of potential required returns associated with single individuals in a state and the rate of filing compliance.

The results of our calibrated probit analysis also reveal evidence of regional variation in filing compliance, with higher compliance among those residing in the Mid-Atlantic division and substantially lower compliance among those residing in the Mountain and Pacific divisions.

Individuals with gross income close to the filing threshold may perceive a relatively low risk of detection if they choose not to file, since information available to the agency is unlikely to definitively show an income tax filing requirement; moreover, any tax balance due is likely to be rather modest. Indeed, the calibrated probit estimates indicate that such individuals are much less likely to file a timely return. Compared to a taxpayer with the mean characteristics of the weighted CPS-ASEC sample, an individual with the same level of burden but with gross income near the filing threshold is estimated to be approximately 40 percentage points less likely to file.

The theoretical framework discussed in Section 4 indicates that a high filing burden can discourage filing compliance. Overall, it appears that burden does, in fact, serve as a deterrent to compliance. Over the thirteen year estimation period, the average real monetized filing burden was about $440. Compared to a taxpayer with this level of burden, an individual facing a real burden of $880 is estimated to be about 7.4 percentage points less likely comply with his or her filing obligation. Plumley (1996) also found a strong negative relationship between a state-level measure of the average filing burden and the state-level filing rate.

Our finding regarding the deterrent effect of filing burden is actually rather nuanced, however. In particular, the results indicate that the estimated deterrent effect of the filing burden is much less pronounced among those who have income near the filing threshold. Although such taxpayers presumably face a lower risk of detection and therefore have a better opportunity to avoid a high filing burden, the results suggest that a high burden actually serves as less of a filing disincentive in their case. This runs counter to the earlier finding of Erard and Ho (2001) that burden poses a greater deterrent to filing among taxpayers near the filing threshold. The likely explanation for this discrepancy is that, in the years between these studies, an increasingly large share of low and moderate income earners has become eligible for rather generous refundable tax credits, such as the Earned Income Tax Credit. Although it is somewhat burdensome to file and claim such credits, the size of the benefit in most cases outweighs the cost of participation. Effectively, a high filing burden among taxpayers near the filing threshold is often an indication of positive incentive to file a return in order to take advantage of a refundable credit.

Eligible taxpayers with three or more children receive a larger Earned Income Tax Credit than those with comparable earnings but fewer children.[20] Consistent with this additional filing incentive, the results indicate that families with three or more children are relatively more likely to file a required tax return.

The above findings are qualitatively similar to the preliminary results we reported in Erard *et al.* (2020) based on an analysis of filing behavior for tax year 2010. However, the pooled calibrated probit analysis employed in the current study also reveals some new insights.

First, beginning in tax year 2009, the EITC for families with three or more qualifying children was increased by 5 percentage points, thereby increasing benefit amounts by as much as $715. Although this increased filing incentive was introduced as a temporary measure, the benefit expansion was ultimately enshrined as a permanent feature of the EITC program. The findings in Table 5 indicate that the expansion of this credit has contributed to a 5.3 percentage point increase in timely filing among households with three or more children.

Second, the Economic Stimulus Act of 2008 was introduced to boost consumer spending and business investment during the Great Recession. One of the Act's provisions entitled filers of tax year 2007 federal individual income tax returns to a rebate of up to $600 for individual filers and $1,200 for married joint filers, plus $300 for each dependent child under the age of 17. The estimation results suggest that the stimulus payment provided a powerful incentive to file in that year: the filing rate for required returns is estimated to have jumped by 1.64 percentage points between tax years 2006 and 2007. This rate subsequently declined by about 0.76 percentage points over the following tax year.[21] It declined even more precipitously over the next two tax years. A widely held belief among tax administrators is that, once a taxpayer is brought into the tax system, that individual will tend to remain in the system. The temporary nature of the filing response to the Economic Stimulus Act of 2008, however, calls this received wisdom into question.[22]

7.2 *Calibrated Multinomial Logit Model Findings*

More than one-third of taxpayers who miss the filing deadline for a given tax year do eventually file their required tax returns. Although different motivations are likely to be at play among taxpayers who file late and those who never file, the few existing studies of filing determinants fail to distinguish between these two types of behavior. In order to separately identify the drivers of late filing and never filing, we have estimated a multinomial logit model of filing compliance. Two sets of marginal effects estimates are provided for this model in Table 5. The first provides the estimated impact of each regressor on the marginal probability of filing a timely return, while the second set provides their estimated impact on the marginal probability of filing a late return.

Overall, the estimated marginal effects for the timely filing probability are qualitatively quite similar to those discussed previously for the calibrated probit model. However, the coefficient of the self-employment earnings dummy is now estimated more precisely. The calibrated multinomial logit results indicate that the presence of a non-trivial amount of self-employment earnings is associated with a 3.6 percentage point reduction in the likelihood of filing a timely return. Given that self-employment earnings are not typically subject to third-party information reporting, it seems plausible that this result may be attributable to a lower perceived risk of detection.

Turning now to the estimated marginal effects for the probability of filing a late return, the results indicate that late filing is relatively more common among taxpayers with self-employment earnings or high levels of gross income. It is also more likely to occur when one resides in a jurisdiction without a state income tax. On the other hand, married individuals and elderly taxpayers are relatively less likely to file after the deadline. There is also a regional pattern to late filing, with a higher incidence among taxpayers residing in the Mid-Atlantic, South-Atlantic, West South-Central, Mountain, and Pacific Census divisions and a lower incidence in the East and West North-Central divisions.

Families with three or more children were relatively more likely to file a timely return and less likely to file a late return from tax year 2009 onwards, perhaps in response to the expanded EITC credit that was available to large families in those years. Similarly, taxpayers were much more likely to file a timely return and less likely to file a late return for tax year 2007, consistent with the substantial filing incentive associated with the economic stimulus payment in that year. On the other hand, taxpayers with income close to the filing threshold and those with relatively high filing burdens were substantially more likely to remain ghosts than to file either a timely or a late return.

7.3 *Accounting for Past Filing Behavior*

Erard and Ho (2001) found evidence of substantial persistence in tax filing behavior. One possible explanation is that taxpayers who have filed in one year may perceive a relatively high risk of detection if they should fail to file a required return in the subsequent year. In fact, the IRS has a "Stop-Filer" program to address such behavior. Another potential explanation is that taxpayers who have previously filed a return are more likely both to be aware of their filing obligation and to adhere to legal requirements.

To control for prior-year filing behavior, we have developed an extension of our calibrated probit methodology that incorporates one's filing history into the parametric specification of the likelihood of filing a timely return. The results in Table 5 reveal substantial persistence in filing behavior over time. Specifically, the likelihood of filing a required return for the current year is estimated to be 44.6 percentage points higher if an individual filed a return for the previous tax year.

Consistent with the other models we have estimated, the results show that monetary incentives can serve as a strong impetus for timely filing. For instance, the economic stimulus rebate is associated with a 1.8 percentage point jump in the overall propensity to file a timely return between tax years 2006 and 2007. The temporary nature of this incentive is reflected in the reversion in the filing rate after tax year 2007. In response to the permanent expansion of the EITC benefit for families with three or more children, the timely filing rate among large families is estimated to have risen by 2.3 percent since it was introduced.

As with the other econometric models that have been discussed, the estimated propensity to file a timely return is substantially lower for married couples (almost 7 percentage points lower). For the most part, the estimated marginal effects of the remaining explanatory variables are qualitatively similar to what was found with the other models, although the effects tend to be more muted. Apparently, the prior-year filing measure captures a portion of the influence that would otherwise be attributed to these variables. In one case (natural log of gross income), the estimated marginal impact has changed from positive to negative after the prior-year filing measure has been introduced.

8. Concluding Remarks

This study has examined the role of ghosts in the US federal income tax machinery. In any given year, an estimated 10 to 12 percent of all US taxpayers with a legal filing obligation fail to submit a timely income tax return. Approximately 35 percent of these ghosts eventually emerge from the shadows and file a late return (sometimes after experiencing an IRS enforcement contact); the remaining 8 to 11 million ghosts remain forever hidden from the tax rolls for that year.

Not only are these ghosts absent from the tax rolls, they are also missing from most theoretical and empirical models of tax compliance behavior. This study sheds new light not only on the size of the ghost population and its implications for federal tax revenue, but also on the drivers of filing noncompliance. In contrast to the few existing empirical studies on nonfiling behavior, this paper explores not only the determinants of timely filing, but also of late-filing behavior, thereby shedding new light on how late-filers differ from individuals who never file. The results provide evidence not only on the roles of socio-economic and demographic factors in influencing filing behavior, but also on the role of financial incentives, such as refundable credits, fiscal stimulus payments, and the monetized value of the filing burden.

The estimation results reveal substantial persistence in filing behavior. In particular, the estimated likelihood of filing a timely return for the current tax year increases by 45 percentage points if the individual filed a return for the previous tax year. At the same time, the results suggest that one-time financial incentives have only a temporary impact on those with a legal filing obligation. This is a very important finding, because it runs counter to the prevailing wisdom that, once a taxpayer has been brought into the system, the taxpayer will continue to file in subsequent years.

The outstanding taxes owed by ghosts are significant. The nonfiling tax gap is estimated to have amounted to more than $37 billion per year over the 2011-2013 period. Even after accounting for enforcement and late filings, as much as $25 billion in taxes is estimated to have gone unreported and uncollected as a result of required returns that have gone unfiled for a given tax year.[23] Although the ghost population as a whole has a substantial tax balance due, many ghosts are actually entitled to tax refunds, owing to their excessive prepayment of taxes and their eligibility for refundable credits. The econometric analysis provides insight into why some taxpayers choose to forgo refunds to which they are entitled. In particular, it finds that a high filing burden can be a significant deterrent to filing a return.

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Endnotes

1 Three noteworthy studies of the magnitude and determinants of individual income tax nonfiling were conducted many years ago: Alm, Bahl, and Murray (1991) on occupational differences in the individual income tax nonfiling rate among self-employed Jamaicans; Plumley (1996) on the underlying causes of variations in the aggregate federal income tax nonfiling rate across states and over time; and Erard and Ho (2001) on the magnitude and determinants of federal individual income tax nonfiling in the U.S.

2 There are some exceptions to this rule, such as when the individual has to file to report self-employment payroll taxes or the receipt of advance payments of certain tax credits.

3 The overall number of timely filers with a legal filing obligation will be undercounted to some degree under this approach as a result of taxpayers who have incorrectly identified their filing status or understated their self-employment or overall gross earnings on their returns. This undercounting of the numerator of the VFR formula will be offset to a significant extent by a comparable degree of undercounting with regard to the denominator.

4 To reduce the lag-time associated with development of the VFR estimates, we perform our comparison against the list of individuals who have filed an individual income tax return within two years of the end of the relevant tax year. The methodology for assessing a filing requirement among individuals who filed after this date is the same as that described below for individuals who never filed a return.

5 Net self-employment earnings are imputed based on prediction equations derived from an econometric analysis of the presence and magnitude of self-employment earnings on filed returns. Estimates of gross self-employment earnings are then obtained by applying gross-up factors derived from filed returns.

6 The imputations of filing status and dependent children to unfiled returns are calibrated to ensure that the overall distribution of filing status by age and number of dependents for filed and unfiled returns combined is consistent with Census tabulations for the overall US population. The reduced filing threshold for taxpayers who are claimed as a dependent on another return is assigned to all unfiled returns involving taxpayers who are of age 21 or younger.

7 For a detailed discussion of the nonfiling tax gap estimation methodology, refer to Internal Revenue Service (2019) and Langetieg, Payne, and Plumley (2016).

8 Although our VFR estimation process relies on a cutoff filing date of no more than two years from the end of the relevant tax year for classification of late-filed required returns (with taxpayers who filed after this date being classified among those who never filed), we rely on an extended cutoff filing date of four years from end of the tax year for identifying late filers under our nonfiling tax gap estimation process.

9 Some portion of the $25.3 billion may have been collected through enforcement efforts that were not revealed in our filing data, and an additional portion ultimately may be collected through future enforcement activities. However, much of this outstanding liability is likely to remain uncollected.

10 These estimates are provided in Langetieg, Payne, and Plumley (2016, p. 19). Owing to the cutoff date employed when identifying late filers and the inability to identify some late filing enforcement cases in the IRTF data, it is likely that these estimates overstate to some degree both the aggregate refund amount for late filers and the aggregate balance due for those who never file.

11 For simplicity, the minimum required federal tax prepayment amount is assumed to be fixed. In practice, it depends on one's overall tax liability, so the tax authority may not be able to detect all instances where insufficient tax has been withheld if the taxpayer has underreported income and no audit has been undertaken.

12 As a practical matter, the detection and penalty risks associated with nonfiling may not be widely understood or especially salient. In a fascinating controlled experiment, Meiselman (2018) finds that nonfiler mailings designed to make these risks more salient and better understood were effective at inducing Detroit residents to file their delinquent city income tax returns. His results also showed that burden reduction (via the mailing of a blank tax return and return envelope to potential nonfilers) improved compliance, while an appeal to civic pride was ineffective.

13 The inclusion of a set of tax year dummies among the explanatory variables enables a solution to this optimization problem that exactly satisfies the equality constraints.

14 We anticipate that taxpayers who filed for the most recent tax year will be more likely to file for the subsequent year, regardless of whether the most recent return was legally required. Therefore, our estimate of the number of filers for tax year *t* is not restricted to those with a legal filing obligation for that year. Rather, it only requires that they had a legal filing obligation for the subsequent tax year. When developing the VFR estimates, we were able to identify all apparent members of the required return population for a given tax year. By matching these individuals against the population of returns filed for the previous year, we are able to assess how many of them actually filed a return for the previous tax year.

15 We estimate all of our models using the NLPQN subroutine in SAS/IML[@]. Erard (2020) proposes a generalized method of moments (GMM) solution for obtaining valid standard errors for calibrated qualitative choice parameter estimates. We implement this solution using the GMM option in the SAS MODEL routine. The estimated standard errors for the marginal effects are then obtained via the delta method.

16 To apply certain alternative qualitative choice estimators for supplementary sampling designs, such as those proposed by Cosslett (1981) and Lancaster and Imbens (1996), one would need to have detailed knowledge of the underlying stratification criteria and other relevant aspects of the sampling design.

17 Even if comparable information on balance due status were available in both data sources, it would be challenging to account for the potential endogeneity of this variable.

18 Taxpayers in our IRTF data sample who report either a filing status of married filing jointly or married filing separately are identified as married filers in our analysis.

19 New Hampshire and Tennessee are included among the states with no income tax, although these two states do currently impose a tax on interest and other investment earnings.

20 Prior to tax year 2009, EITC benefits were largest for families with two or more qualifying children. From that year on, families with three or more qualifying children received a larger benefit than those with 2 qualifying children.

21 Taxpayers that did not claim the stimulus credit in tax year 2007 were permitted to claim it on their tax year 2008 returns.

22 A recent field experiment by Guyton *et al*. (2017) casts additional doubt on this received wisdom. In that study, filing reminder messages that were sent to low-income taxpayers were found to have only a temporary impact on filing compliance.

23 The cutoff date for identifying late-filed required returns under our nonfiling tax gap estimation process is four years from the end of the tax year, and the IRTF data do not always include information on returns that have been filed late in response to enforcement activities. Consequently, there is potential for some of the estimated $25 billion in lost revenue each year to be recovered through late filing and enforcement.

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Figure 1: Estimated Voluntary Filing Rate (VFR), tax years 2001 – 2013

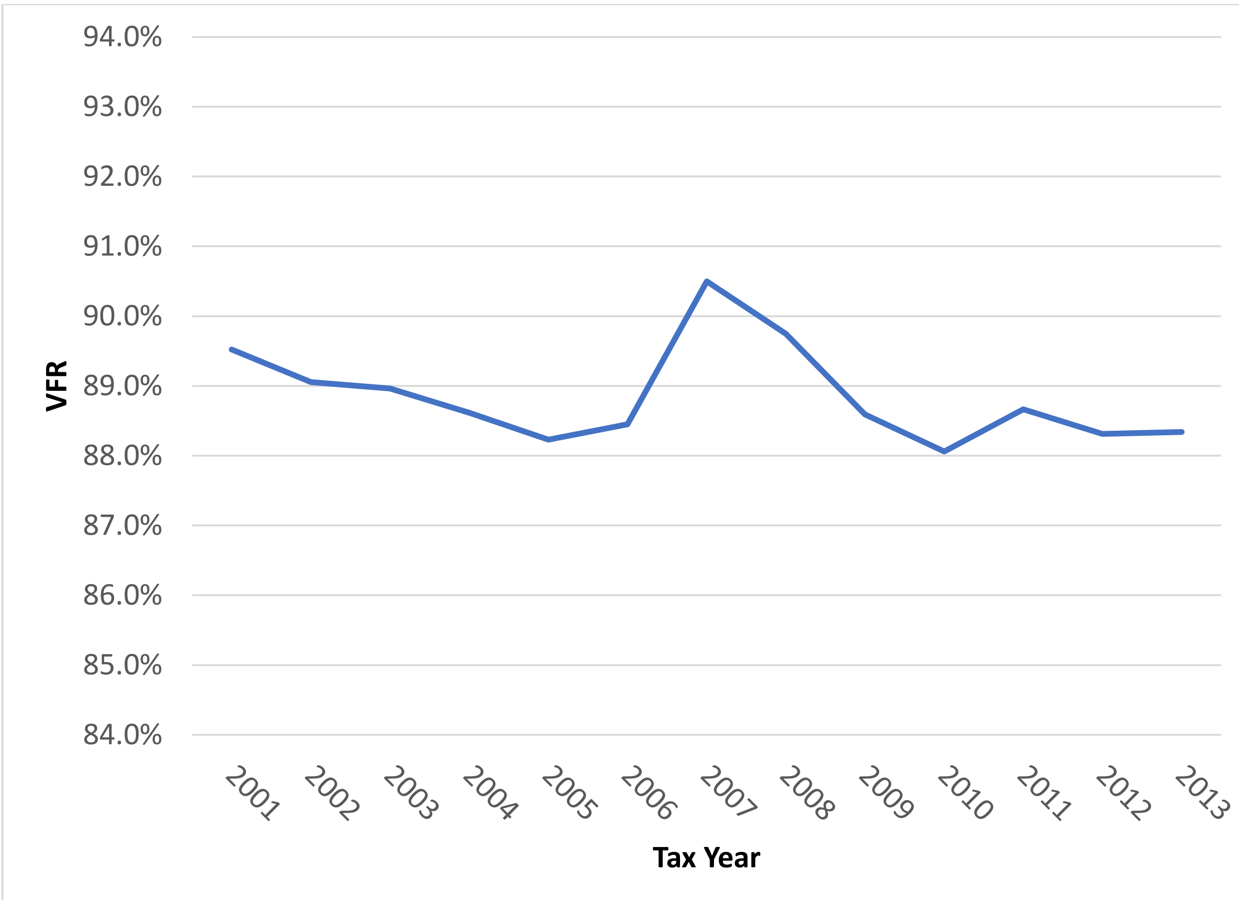

Table 1: Estimated breakdown of federal individual income tax filing behavior, tax years 2001-2013

Tax Year	Millions of Required Returns				Voluntary Filing Rate
	Filed on Time	Filed Late	Never Filed	Total Required	
2001	107.9	4.3	8.3	121.6	89.5%
2002	107.0	4.4	8.7	120.5	89.1%
2003	106.8	4.6	8.7	120.2	89.0%
2004	108.3	4.7	9.3	120.1	88.6%
2005	110.2	4.9	9.8	122.3	88.2%
2006	113.0	5.0	9.8	124.9	88.5%
2007	117.2	4.4	7.9	127.8	90.5%
2008	116.3	5.0	8.3	129.5	89.7%
2009	113.4	5.1	9.5	128.0	88.6%
2010	115.4	5.9	9.8	131.0	88.1%
2011	117.2	5.3	9.7	132.1	88.7%
2012	117.4	5.2	10.3	132.9	88.3%
2013	118.5	4.9	10.8	134.1	88.3%

Source: Estimates developed by the authors.

Table 2: Nonfiler tax gap estimates, three-year average (TY2011-TY2013)

Tax Concept	Amount ($billions)
Total Income	**670.3**
…minus adjustments	-15.8
…minus exemptions	-74.7
…minus itemized deductions	-161.5
Taxable income	**418.3**
Tentative tax	**77.5**
…plus self-employment tax	14.5
…minus non-refundable credits	3.0
Net tax due	**89.5**
…minus tax prepayments	-47.4
…minus refundable credits	-4.6
Overall nonfiling tax gap	**37.4**
Never-filer share of overall gap	**25.3**

Source: Estimates developed by the authors.

Table 3: Nonfiler tax gap by decile, TY2010

Decile	Balance Due ($Billions)	Percent Share
1	0.0	0.1%
2	0.2	0.5%
3	0.2	0.8%
4	0.4	1.4%
5	0.7	2.2%
6	1.0	3.4%
7	1.5	5.3%
8	2.4	8.2%
9	4.3	14.4%
10	18.7	63.7%

Source: Estimates developed by the authors.

Table 4: Average values of explanatory variables by data source

Variable	Data Source	
	IRTF (Timely Filers)	CPS-ASEC (Filers & Nonfilers)
PRIOR YEAR FILER	0.9399	0.8928
AGE 65	0.1380	0.1321
MARRIED	0.4376	0.4629
CHILD3UP	0.0657	0.0650
CHILD3UP*POST2008	0.0268	0.0244
LN(GROSSINC)	10.7041	10.7402
SEFILREQ	0.1224	0.1293
NEARTHRESH	0.0341	0.0374
LN(BURDEN)	6.0768	6.1105
LN(BURDEN)*NEARTHRESH	0.1861	0.2035
NO TAX STATE	0.2001	0.1990
MIDATL	0.1398	0.1379
EASTNC	0.1568	0.1537
WESTNC	0.0692	0.0687
SOUTHATL	0.1915	0.1919
EASTSC	0.0558	0.0556
WESTSC	0.1077	0.1082
MOUNTAIN	0.0677	0.0700
PACIFIC	0.1597	0.1634

Table 5: Estimation Results: Drivers of Filing Compliance

Variable	Calibrated Probit		Calibrated Multinomial Logit				Calibrated Probit with Prior –Year Filing	
	Timely Filing		Timely Filing		Late Filing		Timely Filing	
	Coefficient Estimate	Marginal Effect	Coefficient Estimate	Marginal Effect	Coefficient Estimate	Marginal Effect	Coefficient Estimate	Marginal Effect
PRIOR YEAR FILER							0.4461	0.4461
							(210.67)	(210.67)
AGE65	1.2397	0.1061	2.7734	0.0614	2.5461	-0.0057	0.0315	0.0117
	(17.03)	(60.12)	(22.67)	(62.61)	(20.70)	(-9.89)	(3.07)	(3.09)
MARRIED	-0.4506	-0.0723	-1.0631	-0.0370	-1.2839	-0.0097	-0.1814	-0.0676
	(-23.98)	(-22.26)	(-20.03)	(-14.91)	(-23.01)	(-19.72)	(-22.67)	(-22.71)
CHILD3UP	-0.0519	0.0155	-0.1774	-0.0002	0.0575	0.0042	0.0081	0.0109
	(-2.43)	(5.98)	(-3.98)	(-0.14)	(1.10)	(5.01)	(0.54)	(2.51)
CHILD3UP*POST2008	0.4624	0.0527	0.8013	0.0340	0.4237	-0.0110	0.0624	0.0229
	(11.07)	(15.70)	(9.19)	(16.42)	(4.40)	(-9.92)	(2.66)	(2.69)
LN(GROSSINC)	0.2788	0.0434	0.8337	0.0289	0.9366	0.0051	-0.0145	-0.0054
	(36.17)	(28.24)	(51.59)	(24.50)	(51.84)	(8.99)	(-2.39)	(-2.39)
SEFILREQ	-0.0147	-0.0023	-0.2103	-0.0364	0.4314	0.0287	0.0030	0.0011
	(-1.08)	(-1.06)	(-8.62)	(-27.38)	(15.11)	(34.59)	(0.30)	(0.30)
NEARTHRESH	-2.134	-0.6794	-4.0422	-0.6237	-4.0469	-0.0256	-0.3419	-0.1327
	(-27.30)	(-28.23)	(-22.84)	(-17.38)	(-19.04)	(-11.95)	(-2.24)	(-2.19)
LN(BURDEN)	-0.4763	-0.0742	-1.3028	-0.0391	-1.6400	-0.0143	-0.0357	-0.0133
	(-36.71)	(-27.72)	(-49.05)	(-20.02)	(-58.26)	(-15.83)	(-5.37)	(-5.37)
LN(BURDEN)*NEARTHRESH	0.3276	0.0511	0.6209	0.0223	0.6753	0.0030	0.0549	0.0204
	(22.43)	(21.12)	(19.87)	(12.34)	(17.79)	(3.31)	(1.94)	(1.94)
NO TAX STATE	0.0213	0.0033	-0.0127	-0.0026	0.0467	0.0022	0.0151	0.0056
	(1.34)	(1.35)	(-0.36)	(-1.74)	(1.23)	(4.00)	(1.65)	(1.65)
MIDATL	0.0628	0.0085	0.4965	0.0054	0.8049	0.0116	-0.0006	-0.0002
	(2.04)	(2.02)	(6.96)	(2.13)	(10.45)	(12.20)	(-0.04)	(-0.04)
EASTNC	0.0073	0.0010	0.0223	0.0035	-0.0721	-0.0027	0.0075	0.0028
	(0.26)	(0.26)	(0.38)	(1.42)	(-1.11)	(-3.08)	(0.49)	(0.49)
WESTNC	-0.0751	-0.0113	-0.1869	-0.0027	-0.4013	-0.0061	0.0006	0.0002
	(-2.54)	(-2.57)	(-3.17)	(-0.99)	(-5.84)	(-6.29)	(0.04)	(0.04)

Variable	Calibrated Probit		Calibrated Multinomial Logit				Calibrated Probit with Prior –Year Filing	
	Timely Filing		Timely Filing		Late Filing		Timely Filing	
	Coefficient Estimate	Marginal Effect	Coefficient Estimate	Marginal Effect	Coefficient Estimate	Marginal Effect	Coefficient Estimate	Marginal Effect
SOUTHATL	-0.0772	-0.0016	0.0914	-0.0103	0.4840	0.0146	-0.0068	-0.0025
	(-2.84)	(-2.91)	(1.56)	(-4.22)	(7.47)	(16.04)	(-0.47)	(-0.47)
EASTSC	0.0137	0.0019	0.2206	0.0091	0.1844	-0.0008	-0.0032	-0.0012
	(0.38)	(0.38)	(2.78)	(3.02)	(2.12)	(-0.77)	(-0.17)	(-0.17)
WESTSC	-0.0567	-0.0084	0.1719	0.0006	0.3538	0.0063	-0.0082	-0.0031
	(-1.83)	(-1.84)	(2.49)	(0.22)	(4.68)	(6.24)	(-0.49)	(-.049)
MOUNTAIN	-0.2426	-0.0408	-0.4242	-0.0283	-0.1843	0.0073	-0.0271	-0.0101
	(-8.54)	(-8.83)	(-7.27)	(-9.59)	(-2.77)	(6.86)	(-1.64)	(-1.64)
PACIFIC	-0.2033	-0.0333	-0.3177	-0.0279	0.0680	0.0134	-0.0147	-0.0055
	(-7.73)	(-8.23)	(-5.94)	(-11.20)	(1.13)	(14.52)	(-0.99)	(-0.99)
YR2002	-0.0280	-0.0041	-0.0632	-0.0030	-0.0407	0.0007	-0.0213	-0.0079
	(-10.65)	(-10.65)	(-9.06)	(-11.59)	(-5.60)	(9.85)	(-31.21)	(-31.09)
YR2003	-0.0235	-0.0034	-0.0299	-0.0028	0.0210	0.0018	-0.0190	-0.0070
	(-8.89)	(-8.85)	(-4.25)	(-10.80)	(2.86)	(24.19)	(-27.79)	(27.74)
YR2004	-0.0498	-0.0073	-0.1000	-0.0053	-0.0528	0.0015	-0.0230	-0.0085
	(-18.91)	(-18.62)	(-14.46)	(-19.63)	(-7.30)	(20.66)	(-32.94)	(-32.92)
YR2005	-0.0813	-0.0122	-0.1815	-0.0096	-0.1024	0.0025	-0.0280	-0.0104
	(-30.80)	(-29.54)	(-26.31)	(-33.10)	(-14.17)	(33.32)	(-37.28)	(-37.45)
YR2006	-0.0726	-0.0109	-0.1452	-0.0078	-0.0756	0.0023	-0.0234	-0.0087
	(-27.08)	(-27.05)	(-20.92)	(-28.18)	(-10.46)	(30.17)	(-31.08)	(-31.16)
YR2007	0.0402	0.0055	0.1039	0.0065	0.0085	-0.0030	0.0248	0.0091
	(15.11)	(14.54)	(14.82)	(25.93)	(1.16)	(-43.26)	(30.93)	(30.79)
YR2008	-0.0149	-0.0021	0.0161	-0.0002	0.0391	0.0008	-0.0276	-0.0102
	(-5.49)	(-5.54)	(2.28)	(-0.85)	(5.35)	(11.03)	(-32.32)	(-32.19)
YR2009	-0.1076	-0.0165	-0.1884	-0.0108	-0.0842	0.0035	-0.0392	-0.0145
	(-27.04)	(-26.52)	(-19.00)	(-26.25)	(-8.06)	(27.85)	(-21.94)	(-21.90)
YR2010	-0.1466	-0.0231	-0.2168	-0.0167	0.0121	0.0084	-0.0355	-0.0132
	(-36.67)	(-35.68)	(-21.86)	(-40.03)	(1.15)	(62.27)	(-19.75)	(-19.75)
YR2011	-0.1205	-0.0186	-0.2170	-0.0118	-0.1171	0.0033	-0.0246	-0.0091
	(-29.90)	(-30.02)	(-21.88)	(-28.45)	(-11.21)	(26.11)	(-13.62)	(-13.61)

Variable	Calibrated Probit		Calibrated Multinomial Logit				Calibrated Probit with Prior –Year Filing	
	Timely Filing		Timely Filing		Late Filing		Timely Filing	
	Coefficient Estimate	Marginal Effect	Coefficient Estimate	Marginal Effect	Coefficient Estimate	Marginal Effect	Coefficient Estimate	Marginal Effect
YR2012	-0.1469 (-36.20)	-0.0231 (-36.00)	-0.3034 (-30.40)	-0.0149 (-33.32)	-0.2224 (-21.15)	0.0024 (19.36)	-0.0398 (-22.01)	-0.0148 (-21.98)
YR2013	-0.1582 (-37.13)	-0.0251 (-36.96)	-0.3834 (-37.59)	-0.0161 (-32.13)	-0.3816 (-35.46)	-0.0006 (-4.52)	-0.0353 (-18.92)	-0.0131 (-18.92)
CONST	1.4717 (23.73)		2.3618 (17.21)		-0.1012 (-0.64)		0.4526 (9.63)	
Sample Size	2,469,715		2,500,000				2,469,715	