DO PRODUCTS OFFERING EXPEDITED REFUNDS INCREASE INCOME TAX NONCOMPLIANCE?*

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AN ESTIMATED 20 MILLION INDIVIDUAL INCOME taxpayers utilize various types of bank products (Refund Anticipation Loans (RALs) and Refund Anticipation Checks/Cards (RACs)) to obtain their income tax refund. An RAL is a short-term loan from a bank secured by the taxpayer's expected refund and generally expedites the receipt of that refund. The taxpayer contracts with the bank for the loan and receives the funds a day or two after applying for the loan (assuming it is approved). The refund is then sent to a specified account held by the lender to pay off the loan. With an RAC, the bank opens an account for the taxpayer into which the tax refund is direct deposited. The taxpayer is then given a check or a debit card for the refund amount less fees and can access these funds once the refund is electronically deposited into this account. Use of an RAC could expedite refunds for taxpayers who do not have available bank accounts. Both types of bank products have been criticized by consumer groups because their associated fees translate into very high implicit annual interest rates for refund amounts provided to the taxpayer a few weeks earlier than if they received a paper check from the Internal Revenue Service. The time differential is even smaller for taxpayers who have their refund directly deposited to their personal bank account. Some critics have called for regulation or even the abolition of these bank products in the name of consumer protection.

However, from a tax administration standpoint, taxpayer utilization of bank products such as RALs and RACs may have several, possibly offsetting, effects. It is possible that the use of RALs and RACs may increase the rate of electronically filed returns, since providers of these bank products want to receive the refund amounts as soon as possible, to cover the amount provided to the taxpayer in advance of the refund being paid. Increasing the number of electronically filed returns is a key component to help improve the efficiency of tax administration by reducing costs and permitting more comprehensive use of tax return data. Moreover, bank product users are more likely to use direct deposit than other returns (this is not a surprise given that the financial institution setting up the bank product desires access to the funds as soon as possible). While bank product users made up around 14 percent of all individual income tax returns in Tax Year 2004, they were responsible for about one-third of all direct deposits made by the IRS that year. Direct deposit of refunds reduces processing costs for a tax administrator.

On the other hand, use of RALs and RACs may also lead to less compliant behavior on the part of taxpayers and perhaps the preparers who facilitate access to these bank products. This could occur if the ability to receive refunds on an accelerated basis led taxpayers or preparers (acting as an agent of the taxpayer) to make inappropriate claims to inflate refund amounts. Tax administrators need to untangle these effects in order to objectively evaluate the net benefits (or costs) of these products.

The use of bank products (RALs and RACs) has been increasing over time as shown in Figure 1. Between Tax Year 2001 and Tax Year 2005, the number of returns using bank products grew from 15 million to approximately 20 million (or from 11 percent of individual income tax returns to nearly 15 percent). For Tax Year 2004, IRS data can be used to distinguish between RALs and RACs (for other years in the time series, these two bank products cannot be broken out separately). Individual taxpayers made use of 10.6 million RALs and 7.5 million RACs in Tax Year 2004.[1]

Taxpayers who make use of bank products have some characteristics that differ from those of the larger population of individual income tax filers. Table 1 shows some of these characteristics for the 129 million individual income tax returns filed for Tax Year 2004 in 2005. RAL users, on average, have lower adjusted gross incomes and are younger than taxpayers who use RACs, with larger differences observed between taxpayers using RALs and those eschewing bank products entirely. Most RAL users

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Figure 1: **Taxpayers' Use of Bank Products for Tax Years 2001-2005**

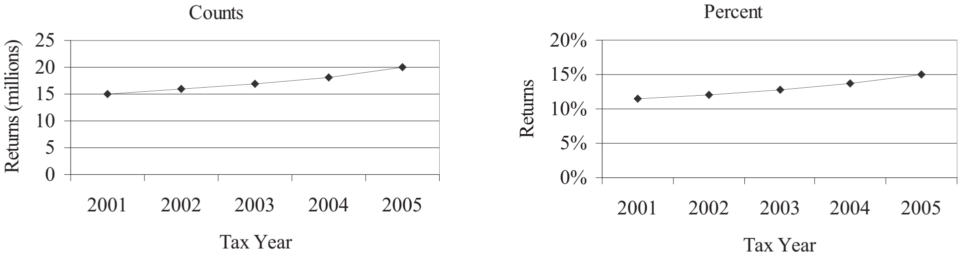

Table 1

Characteristics of Taxpayers by Bank Product Type for Tax Year 2004 Returns Filed in 2005 (dollar amounts rounded to nearest hundred)

	No Bank Product	*RAL*	*RAC*
Number of Returns (millions)	110.7	10.6	7.5
Average Adjusted Gross Income	\$55,200	\$22,400	\$32,200
Average Age	45	35	36
Used a Paid Preparer	56%	94%	57%
Single or Head of Household	56%	79%	69%
Male	47%	43%	41%
Female	53%	57%	59%
Live in the South	33%	53%	44%
Percent Audited	0.6%	2.4%	2.5%
Claimed EITC w/Qualifying Children	7.5%	58.4%	40.4%

used a paid preparer, and RAL users were more likely to use a paid preparer than RAC users or than taxpayers who did not use a bank product. RAL and RAC users are proportionately more likely to claim the earned income tax credit (EITC) with children (which results in a larger credit amount). For instance, about half the returns claiming the EITC with qualifying children use a bank product, while only around 7 percent of returns not claiming the EITC with qualifying children use a bank product.

We utilize three separate data sets to test the hypothesis that income tax noncompliance is associated with individual taxpayer utilization of RALs and RACs. These data sets involve individual income tax micro data and permit us to hold constant the effects of demographic and economic variables. Moreover, these data sets permit us to begin to untangle the effect of the various elements associated with taxpayer use of a bank product to get an accelerated income tax refund. And by taking three separate looks at the relationship between the use of bank products and overall compliance, we increase our confidence that any observed effects are real and significant and not due to the specific model configurations used in the analysis.

One data set involves the Tax Year 2001 Individual Income Tax Reporting Compliance study carried out by the IRS through its National Research Program. We build upon work examining the effect of paid preparers on tax compliance by Masken, Guyton, and Mazur (2007)[2] by adding variables to capture the use of bank products in a standard regression framework. This part of the analysis provides a statistically valid look at the entire individual taxpayer population for Tax Year 2001, but the portion of the sample consisting of taxpayers using bank products is relatively small. Moreover, this data set does not permit us to separate out the effect for RALs from that of RACs.

The second data set looks at all individual income tax returns that were filed for Tax Year 2004 and subject to examination. This is a robust data set, but only includes returns that were subject to examination, which introduces selection bias because the process by which returns are selected for audit is not random. We use propensity scores to match taxpayers in the test group (those who use RALs or RACs) to a control group of similar taxpayers who do not make use of such bank products. This approach allows us to control for many potential explanations for observed noncompliance and to focus attention on the compliance differences associated with users of RALs and RACs.

Characteristics of taxpayers in this data set are shown in Table 2. Similar to the entire population, audited taxpayers using bank products are younger and have lower income than those who do not use a bank product. In addition, bank product users whose returns are audited are less likely to file a joint return than those who avoid bank products.

The third data set is a random sample of earned income tax credit recipients with qualifying children, who make up a very large segment of the population of RAL and RAC users. The data cover Tax Year 2004 and follow this set of taxpayers through the return filing and audit cycle. This is a very rich data set that includes additional information used to select returns for audit and allows us to address the selection bias issue. We again use propensity scores to match taxpayers in the test group (those using bank products) to similar control group taxpayers (those not using bank products). Similar to the second data set, this approach permits us to control for many potential explanations for differing rates of noncompliance but, in addition, it also allows us to control for audit selection bias.

Selected characteristics of this data set are shown in Table 3. Once again, bank product users are younger and have lower incomes on average than those not choosing a bank product to expedite their refund. Moreover, RAL and RAC users are less likely to file a joint return and are more likely to live in the South.

LINEAR REGRESSION MODEL

Through its National Research Program (NRP), the IRS conducted a reporting compliance study

Table 2
Characteristics of Taxpayers Audited for Tax Year 2004
(counts and dollar amounts rounded to nearest hundred)

	No Bank Product	*RAL*	*RAC*
Number of Returns	657,200	257,800	185,000
Average Adjusted Gross Income	$86,700	$18,200	$20,000
Average Age	43	33	34
Single or Head of Household	61%	94%	88%
Male	63%	71%	63%
Female	37%	29%	37%
Live in the South	35%	55%	48%

Table 3
Characteristics of Taxpayers Claiming EITC with Qualifying Children in Tax Year 2004
(counts and dollar amounts rounded to nearest hundred)

	No Bank Product	*RAL*	*RAC*
Number of Returns	8,330,700	6,179,700	3,027,800
Average Adjusted Gross Income	$17,800	$16,000	$16,300
Average Age	39	34	35
Single or Head of Household	65%	83%	81%
Male	24%	29%	25%
Female	76%	71%	75%
Live in the South	37%	56%	49%

on Tax Year 2001 individual income tax returns. The resulting full data set consists of about 46,000 randomly selected income tax returns that were subject to a thorough analysis to determine reporting compliance behavior. We used subsamples of this full data set to (1) focus only on taxpayers who claimed a refund (since these are the only ones who could make use of a bank product); and (2) develop separate models for noncompliance of reported income tax liability and noncompliance on reported refundable tax credits (the earned income tax credit and the additional child tax credit).

The conceptual models used for misreported tax liability and misreported refundable credits are similar. For both, we view the taxpayer's observed noncompliance to be a function of their risk tolerance and the taxpayer's opportunities to be noncompliant. That is, we view taxpayers as making more or less rational choices about their level of noncompliance when reporting their income tax.[3] We hypothesize that a taxpayer's risk tolerance is associated with:

- Age (where younger taxpayers would be more risk tolerant)
- Gender (where males would be more risk tolerant)
- Filing status (where joint filers would be less risk tolerant)
- True tax liability (where the larger the true income tax liability, the greater the risk tolerance)

We also hypothesized that a taxpayer's risk tolerance would be associated with their perception of the chance of being audited and their level of education, but were unable to operationalize these concepts on a micro level.

In modeling the relationship with opportunities for noncompliance, we hypothesize that these opportunities are associated with:

- Preparation method (though it is unclear whether using a paid preparer increases or decreases the opportunity set for noncompliance in all instances[4])
- Complexity and transparency of the taxpayer's return (where increased complexity and decreased transparency would provide greater opportunities for noncompliance)

We used conventional linear regression modeling to test the hypothesis that taxpayers who use bank products are less compliant than taxpayers who do not make use of these products.

The general form of the models is:

$$y = \acute{a} + p'\,\ddot{e} + X_1'\hat{a}_1 + X_2'\hat{a}_2 + X_3'\hat{a}_3 + \mathring{a},$$

where

- y is a vector of values for the dependent variable (either misreported tax liability as a percent of income or misreported tax credit amounts);
- $\acute{a}$ is an intercept vector;
- p' is a vector of indicators for whether or not the taxpayer used a bank product;
- $\ddot{e}$ is the vector of coefficients indicating the impact of bank product usage on the dependent variable;
- X_1 is a matrix of values for the variables associated with risk tolerance;
- X_2 is a matrix of values for the variables associated with opportunities for noncompliance;
- X_3 is a matrix of interactions between bank product usage and (p') and the variables in X_1, and X_2;[5]
- $\mathring{a}$ is a vector of error terms.

For the tax model, the data set consisted of 15,062 returns (representing 36.6 million taxpayers) in the NRP Tax Year 2001 database where the taxpayer had underreported their income tax liability and had also claimed a refund. Upon examination, these returns had an adjustment to the income tax liability, and the corresponding dependent variable was defined as the amount of underreported income tax (true income tax liability less income tax liability as reported by the taxpayer) as a fraction of true total income (as determined by the IRS). Table 4 shows the coefficients for the tax model. The R-square for this model was 0.52.

As shown in Table 4, taxpayers who used bank products were more noncompliant than those who did not, but there is no significant additional effect from using a paid preparer. Moreover, unmarried taxpayers are more noncompliant than those filing joint returns. Older taxpayers are less noncompliant while those living in the South are more noncompliant. Taxpayers who have greater amounts of nontransparent adjustments to income (where there is

Table 4
Regression Coefficients for the NRP Tax Year 2001 Tax Model

(True Tax -- Reported Tax) / True Total Income × 100
Mean = 2.7%
R-square = 0.52

Parameter	*Estimate*	*t Value*
Intercept	3.54*	19.49
Bank Product	1.04*	9.23
No Bank Product (baseline)	—	—
Paid Preparation	-0.02	-0.27
Self Preparation (baseline)	—	—
Unmarried Female	0.72*	7.12
Unmarried Male	0.92*	8.59
Married (baseline)	—	—
Region Northeast	0.2	1.56
South	0.22*	2.34
West	-0.03	-0.31
Midwest (baseline)	—	—
Refund ≤ $700	-1.85*	-13.48
Refund $700 ≤ $1800	-2.29*	-18.22
Refund $1800 ≤ $4000	-2.49*	-20.33
Refund > $4000	-2.49*	-17.72
Owe $1000 < $3500	3.21*	12.63
Owe $3500 < $10,000	7.01*	16.52
Owe ≥ $10,000	15.57*	9.3
Owe $0 < $1000 (baseline)	—	—
Age	-0.01*	-3.09
Total Number Forms Filed	-0.09*	-2.67
Positive Non-transparent Income	0.00	0.57
Negative Non-transparent Income	0.01	1.05
Positive Non-transparent Adjustments	0.23*	2.91
Negative Non-transparent Adjustments	-0.32*	-9.97

* Significant at the 5 percent level.

no information reporting, such as moving expenses) are more noncompliant. Finally, taxpayers who have larger amounts owed based on their true income tax tend to be more noncompliant, as well.

For the credit model, the dataset consisted of 3,310 returns (representing 9.1 million taxpayers) in the NRP Tax Year 2001 database where the taxpayer had overreported their total credits and claimed an income tax refund. Upon examination, these returns had an adjustment made to the amount of tax credit claimed, and the corresponding dependent variable was the difference in dollars between the credit amount claimed by the taxpayer and the true credit amount (as determined by the IRS). Unlike the tax model, the amount of true income is included as a potential explanatory variable in the credit model, instead of being used to scale the amount of observed noncompliance. Table 5 shows the coefficients for the credit model. The R-square for this model was 0.39.

As shown in Table 5, taxpayers who used bank products were more noncompliant than those who did not. Similar to the tax model results, there was no additional effect on noncompliance from using a paid preparer. Unlike the tax model, the additional impact of age and filing status was not significant. Similar to the tax model, larger amounts of true tax liability were associated with more noncompliance

Table 5
Regression Coefficients for the NRP Tax Year 2001 Credit Model

Mean Difference between Credit Claimed and True Credit = $1,565
R-square = 0.39

Parameter	*Estimate*	*t Value*
Intercept	679*	3.04
Bank Product	238*	2.96
No Bank Product (baseline)	0	.
Paid Preparation	-54	-0.71
Self Preparation (baseline)	0	.
Unmarried Female	-19	-0.22
Unmarried Male	-3	-0.03
Married (baseline)	0	.
Region Northeast	54	0.48
South	184*	1.96
West	65	0.62
Midwest (baseline)	0	.
Two or more Children at Home Exemptions	1944*	15.64
One Child at Home Exemption	1193*	10.55
No Child at Home Exemptions (baseline)	0	.
Refund ≤ $700	-92	-0.79
Refund $700 ≤ $1800	-125	-1
Refund $1800 ≤ $4000	-1139*	-9.27
Refund > $4000	-1583*	-11.18
Owe $1000 < $3500	235	1.63
Owe $3500 < $10,000	1040*	6.97
Owe ≥ $10,000	1650*	4.17
Owe $0 < $1000 (baseline)	0	.
Age	0.13	0.04
Total Number Forms Filed	-42.93	-1.84
Positive Non-transparent Income	0	0.63
Negative Non-transparent Income	0.02*	3.78
Positive Non-transparent Adjustments	-0.02	-0.61
Negative Non-transparent Adjustments	1.75*	10.59
True Total Income	-0.03*	-6.97
True Total Tax	0.07*	5.45
Intercept	679*	3.04
Bank Product	238*	2.96

* Significant at the 5 percent level.

as was residing in the South. Larger amounts of true income were associated with less noncompliance. Claims of exemptions for children living at home were associated with greater noncompliance, since these refundable credits are based on the existence of children with whom the taxpayer resides, and a major source of noncompliance are claims where the taxpayer cannot establish that he or she lives with the qualifying child(ren).

In summary, both models using the Tax Year 2001 NRP dataset indicate that use of bank products is associated with greater amounts of detected noncompliance.

PROPENSITY SCORING

While the traditional models using the Tax Year 2001 NRP data provided interesting results, it was not possible to differentiate between the two types of bank products with this data. Furthermore, it is quite possible that taxpayers who used RALs had different behavior than those who used RACs. The only data available to us where we could differentiate between the two types of bank products was for Tax Year 2004, however, the only compliance data available was from operational audits conducted by the IRS. Unlike the NRP reporting compliance studies, operational audits are not selected randomly but rather the returns are selected because they exhibit characteristics associated with noncompliance. Therefore, we had to address audit selection bias in order to use this data. To do this, we used propensity scoring, which computes the conditional probability of receiving a treatment given a vector of covariates.

Propensity scoring was first introduced by Rosenbaum and Rubin (1983) to provide an alternative method for estimating treatment effects when treatment assignment is not random.[6] This approach was initially intended for the medical field where it is not always possible to design a controlled experiment. For example, the relationship between smoking and lung cancer may be of interest, but it is not feasible (or ethical) to set up an experiment a priori where one group of test subjects would be told to smoke while another group with similar characteristics was told not to. In this example, the aim of the propensity score matching approach is to identify a "control group" of nonsmokers who, except for their smoking behavior, are similar to the smokers in the "treatment group".

The general approach used here is to develop a score for the propensity to have the treatment (in this case, to use a bank product). The propensity score is defined as the predicted probability of being in the treatment group as a function of observable characteristics. The next step is to then match taxpayers who received the "treatment" (used a bank product) to taxpayers with a similar propensity score, but who did not use a bank product (these serve as the control group). The final step is to compare the audit results for each matched pair.

We applied these propensity scoring techniques to both our Tax Year 2004 data sets. The first data set included all Tax Year 2004 returns that were selected for audit and where the audit was complete as of April 2008. We looked at taxpayers who prepared the returns themselves and taxpayers who used a paid preparer. Taxpayers who used a volunteer preparer or where IRS prepared the return were excluded. Taxpayers with an address outside of the United States were also excluded (primarily these are taxpayers in the military). Taxpayers using RACs and RALs were modeled separately.

The second data set included a 10 percent sample of all taxpayers who timely filed a Tax Year 2004 return that claimed the EITC with Qualifying Children. This data set included information used in the audit selection process that is not readily available in other data sets. Because taxpayers who use bank products are selected for audit at a significantly higher rate than those who do not use bank products, we believed this data set had pertinent information that would help us control for this selection bias. We analyzed each data set separately, but followed the same general methodology.

Developing the Propensity Scores

For each data set, returns were first separated into groups and subgroups. For the first data set (containing all audited returns filed in Tax Year 2004), the returns were separated into those selected for audit by the EITC audit selection mechanism and those selected by some other mechanism. This was necessary because the selection rules are quite different for returns claiming the EITC and other returns. For the second data set, the returns were divided between taxpayers who used a paid preparer and those who prepared the return themselves. Each of these groups was further separated into subgroups that were correlated to both the use of a bank product and noncompliance (based on the Tax Year 2001 NRP data analysis described above). These variables included region (Northeast, Midwest, South, West), filing status (married or widowed vs. single or head of household), and if the taxpayer was single or head of household whether the taxpayer was male or female (married taxpayers are considered to be gender neutral).

To calculate the propensity score (intuitively, the probability that a taxpayer used an RAL or an RAC), we started with a traditional logistic regression model using stepwise regression for each subgroup. For the second data set (the one focused on EITC claimants), many of the variables on the file were binomial, resulting in many taxpayers receiving the same score. Two continuous variables—age and balance due with the return—were added as independent variables in the logistic regression model, so that a greater number of unique scores would be calculated by the model.

Given that logistic regression models are additive, we believed that these models could potentially miss important nonlinear relationships, such as interaction effects. Therefore, we also used a nonparametric model that could account for these types of relationships. The procedure used was the decision tree model chi-squared Automatic Interaction Detector (CHAID). We developed different CHAID models for two of the main groups in each data set. For the data set including all audited returns, we developed a CHAID model for the group selected by the EITC audit selection mechanism and one for the rest of the returns. For the data set focused on returns claiming the EITC, we developed a CHAID model for returns using a paid preparer and another one for self-prepared returns.

Once we had developed the two different types of models and separately scored each return, a composite score was created by adding the parametric (regression-based) and nonparametric (CHAID model) scores together. To test whether the composite score was better than the individual scores, we took a subgroup from the EITC data set, scored them using each model, and then did relatively a simplistic match. The results in Table 6 show that the composite score generally reduced the selection bias more than either of the individual scores. That is, both the regression model and the CHAID model reduced the differences observed between RAL users and taxpayers using no bank products for many important variables by controlling for some underlying relationships. But, the composite scoring technique generally performed at least as well as either of the two models and sometimes better than both. This provides support for using the composite scores in the analysis.

Matching the Treatment Group to a Control Group

For both data sets we used radius matching with increasing calipers in order to match tax returns with similar propensity scores. The caliper used for this matching process was the Euclidean distance between scores. The general approach was to split the file into treatment group (taxpayers who used bank products) and control group candidates (taxpayers who did not use a bank product). Then each treatment group taxpayer was matched to all potential control group candidates within a given caliper. We started with a caliper of 0 (where the propensity scores would indicate exact matches) then increased it to .000000001 (so the propensity scores were very close) and continued the process by increasing the caliper by a factor of ten each time. Once a treatment group member was matched to one or more control candidates,

Table 6
Comparison of Scoring Methods in Reducing Bias

	Raw Data	*Logistic Regression*	*CHAID*	*Composite*
Balance Due Amount				
No Bank Product	-$3,229	-$3,695	-$3,566	-$3,694
RAL	-$3,741	-$3,740	-$3,736	-$3,732
Bias	**-16%**	**-1%**	**-5%**	**-1%**
AGI Amount				
No Bank Product	$17,893	$16,466	$16,954	$16,450
RAL	$16,440	$16,447	$16,457	$16,480
Bias	**8%**	**0%**	**3%**	**0%**
Average Age of Primary Taxpayer				
No Bank Product	37.4	34.2	36.8	35.2
RAL	34.8	34.8	34.8	34.8
Bias	**7%**	**-2%**	**5%**	**1%**
Filing Status = Head of Household				
No Bank Product	0.64	0.77	0.78	0.79
RAL	0.81	0.81	0.81	0.81
Bias	**-27%**	**-5%**	**-4%**	**-3%**

the process was completed for this observation. Control group candidates were never removed from the process (that is, the process used was matching with replacement).

Estimation

The matching process produced a large pool of matches. While estimates for variable means and variances for the treatment group are stable, estimates for the control group may vary depending on which match is used in the computation. In order to get stable point and variance estimates, we used 1000 Monte Carlo simulations to randomly select one control group match for each return with a bank product (treatment group), resulting in 1000 data sets. The mean and variance of the audit results was calculated for each of these data sets, and the averages of these means and variances are used for the overall estimates.

Results

In Tax Year 2004, it was possible for taxpayers who did not use a paid preparer to receive an RAL. However, this situation will not be possible in the future.[7] Therefore, our principal findings for RALs focus only on those taxpayers who used a paid preparer. It is possible for a taxpayer to receive an RAC without going to a paid preparer, therefore we show both paid preparer and self-prepared returns in our findings for RACs. However, a final table in this section includes self-prepared returns and returns prepared by a paid preparer for taxpayers using RALs as well as for taxpayers using RACs.

The results for all audited Tax Year 2004 returns are shown in Table 7. Audits of RAL users resulted in a change in net tax liability (including tax credits) 88 percent of the time compared to 76 percent for taxpayers who did not use a bank product. The average amount of the adjustment for RAL users was also higher than non-bank product users by about $675. However, when one looks at how the audit result was achieved, there are striking differences between taxpayers using RALs and those who do not use a bank product. Audit outcomes due to undeliverable notices were twice as prevalent for RAL users. RAL users also defaulted at a higher rate.[8] When we control for the disposition of the audit, the difference in average adjustments is not as dramatic. For those who agreed with the adjustment or defaulted, the difference between RAL users and taxpayers who did not use bank products is reduced to about $250 and the difference is about $180 for those whose notice was undeliverable.

The results for taxpayers using RACs show a slightly higher percentage of audit adjustments than taxpayers who do not use bank products. Taxpayers using RACs had a slightly higher average audit adjustment and the default and undeliverable notice rates were also slightly higher than for taxpayers not using bank products. However, unlike the situation for taxpayers using RALs, when we control for the disposition of the audit, there does not appear to

Table 7
Results of Propensity Scoring Analysis Using Tax Year 2004 Audited Returns

	Percent with Adjustments		*Average Adjustment*	
	No Bank Product	*RAL and Paid Preparer*	*No Bank Product*	*RAL and Paid Preparer*
Audit Resulted in Adjustment	76%	88%	$2,488	$3,165
Taxpayer Agreed with Adjustment	*20%*	*16%*	*$2,561*	*$2,806*
Taxpayer Defaulted	*52%*	*63%*	*$3,504*	*$3,749*
Audit Notice Undeliverable	*4%*	*8%*	*$3,565*	*$3,747*
	Percent with Adjustments		*Average Adjustment*	
	No Bank Product	*RAC*	*No Bank Product*	*RAC*
Audit Resulted in Adjustment	76%	81%	$2,363	$2,526
Taxpayer Agreed with Adjustment	*22%*	*21%*	*$2,613*	*$2,637*
Taxpayer Defaulted	*49%*	*54%*	*$3,294*	*$3,230*
Audit Notice Undeliverable	*4%*	*6%*	*$3,279*	*$3,235*

be any appreciable difference in the average adjustment between RAC users and taxpayers not using bank products. In fact, in cases where the taxpayer defaulted or the notice was undeliverable, taxpayers who did not use a bank product had somewhat higher average adjustments.

The results of the propensity-scoring based analysis for taxpayers who claimed EITC with qualifying children in Tax Year 2004 are displayed in Table 8. These results echo the results we found for all tax returns filed in Tax Year 2004 that were subject to audit. RAL users had higher overall average adjustments, defaulted at a higher rate, and their notices went undelivered at more than twice the rate of taxpayers not using bank products.

While Table 8 shows that the difference in the overall average adjustment for taxpayers using RALs is significantly larger than the average adjustment for taxpayers who did not use a bank product (approximately $900), this figure may be overstated. One of the premises of propensity scoring is that there is a relatively small treatment group and a relatively large pool of control group candidates to choose from. However, because taxpayers who use RALs were audited at a higher rate than the population as a whole, we actually had more treatment subjects than control candidates in several of the subgroups.

Consequently, we reversed the matching process as a form of sensitivity analysis. That is, we treated taxpayers with no bank product as the treatment group and those using RALs as the control group. When this is done, the results were directionally the same, but not as large in magnitude. With this "reverse" matching, the overall average audit adjustment for taxpayers not using bank products was $2,320 compared to $2,775 for matched RAL users. While the RAL users had a larger average audit adjustment, the difference was about half ($455) of what we originally found. This result from the "reverse" matching supports the hypothesis of there being a significant effect, but leaves open the exact magnitude.

For taxpayers using RACs, we see the average audit adjustment for taxpayers using RACs was slightly lower than for taxpayers who did not use a bank product. This holds true even when we control for the disposition of the audit. The implication is that RAC users appear to be no more noncompliant than EITC claimants who do not use bank products.

Table 9 shows the results of the propensity score analysis that included both RAL users who used a paid preparer and RAL users who prepared their own return. For taxpayers who use an RAL, there is not a very large compliance difference based on preparation method (paid preparer vs. self-prepared). However, for taxpayers who do not make use of a bank product, it appears that self-prepared returns are somewhat more noncompliant.

Table 8

Results of Propensity Scoring Analysis Using Tax Year 2004 Random Sample of EITC Claimants with Qualifying Child(ren)

	Percent with Adjustments		*Average Adjustment*	
	No Bank Product	*RAL and Paid Preparer*	*No Bank Product*	*RAL and Paid Preparer*
Audit Resulted in Adjustment	73%	90%	$2,483	$3,378
Taxpayer Agreed with Adjustment	*16%*	*13%*	*$2,786*	*$3,128*
Taxpayer Defaulted	*52%*	*67%*	*$3,536*	*$3,883*
Audit Notice Undeliverable	*4%*	*9%*	*$3,680*	*$3,858*
	Percent with Adjustments		*Average Adjustment*	
	No Bank Product	*RAC*	*No Bank Product*	*RAC*
Audit Resulted in Adjustment	76%	81%	$2,581	$2,574
Taxpayer Agreed with Adjustment	*19%*	*15%*	*$2,981*	*$2,701*
Taxpayer Defaulted	*52%*	*58%*	*$3,476*	*$3,280*
Audit Notice Undeliverable	*4%*	*7%*	*$3,494*	*$3,220*

Table 9
Results of Propensity Scoring Analysis by Preparation Method

	Percent with Adjustments		*Average Adjustment*	
	No Bank Product	*RAL*	*No Bank Product*	*RAL*
Tax Year 2004 Audited Returns				
Audit Resulted in Adjustment	76%	88%	$2,509	$3,168
Taxpayer Used Paid Preparer	*76%*	*88%*	*$2,488*	*$3,165*
Taxpayer Self Prepared	*82%*	*91%*	*$2,830*	*$3,217*
Tax Year 2004 Random Sample of EITC Claimants with Qualifying Child(ren)				
Audit Resulted in Adjustment	74%	90%	$2,511	$3,376
Taxpayer Used Paid Preparer	*73%*	*90%*	*$2,483*	*$3,378*
Taxpayer Self Prepared	*86%*	*90%*	*$2,997*	*$3,337*

SUMMARY

The traditional linear regression modeling approach shows a correlation between taxpayers using bank products (RALs and RACs) and noncompliance. However, the data used in this methodology does not allow us to differentiate between the two products and it is possible that the correlation observed is dampened by combining the effects from taxpayers using RALs with taxpayers using RACs.

The propensity scoring methods indicate that there is a significant correlation between taxpayers who use RALs and noncompliance. RAL users are 27 percent to 36 percent more noncompliant than taxpayers who do not use a bank product. These methods do not indicate a similarly significant correlation for taxpayers who use RACs compared to those who do not use a bank product.

Our analysis indicates that noncompliance is higher among taxpayers using RALs. We take this as an indicator that RALs provide increased benefits for these taxpayers and thus may encourage some taxpayers to become more noncompliant. We cannot conclude that the availability or utilization of RALs ***causes*** noncompliance. It is possible that taxpayers who are inclined to be noncompliant tend to make use of RALs to more quickly obtain the benefits of that noncompliance, and even if RALs were not available, would still be noncompliant.

Notes

[1] In future years, the IRS will be able to distinguish RALs from RACs using tax return information.

[2] Presented at the November 2007 meeting of the National Tax Association.

[3] This reasoning is derived from Allingham and Sandmo (1972). A thorough review is presented by Andreoni, Erard, and Feinstein (1998).

[4] This is described in detail in Klepper, Mazur, and Nagin (1991).

[5] The initial specification included the interaction terms (X_3), and we estimated models that included these effects (e.g., presence of a bank product and age or marital status/gender). However, the inclusion of these variables did not materially affect our results and they tended to make the model unwieldy and the coefficients difficult to interpret. Accordingly, the results of these models are not presented here. However, these results are available upon request from the authors.

[6] Rosenbaum and Rubin (1983).

[7] In Tax Year 2004, taxpayers were able to arrange an RAL through online preparation services provided by the Free File Alliance, a consortium of software providers who coordinate with the Internal Revenue Service to offer no-cost electronic preparation and filing of individual income tax returns.

[8] A default occurs when a taxpayer does not respond to an IRS notice or otherwise stops communicating with the IRS.

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