Session 4. Creative Use of Non-Tax Data Sources

Moderator: Emily Lin  
U.S. Treasury Office of Tax Analysis

Supplementing IRS Data with External Credit Report Data in Employment Tax Predictive Models  
Curt Hopkins  
IRS, SB/SE

Better Identification of Potential Employment Tax Noncompliance Using Credit Bureau Data  
Saurabh Datta  
IRS, RAAS

Estimating the Effects of Tax Reform on Compliance Burdens  
Daniel Berger  
Tax Policy Center

Counting Elusive Nonfilers Using IRS Rather Than Census Data  
Mark Payne  
IRS, RAAS

Discussant: Adam Isen and Emily Lin  
U.S. Treasury Office of Tax Analysis
SB/SE Strategic Analysis & Modeling Group

Supplementing IRS Data with External Credit Report Data in Employment Tax Predictive Models

Curt Hopkins & Ken Su
Data Sources

External Data Set Secured by RAAS

- Over 275,000 Businesses
- 32 Strata
- 8 Prior Quarters Data
- 3 Credit Scores (Overall, Finance & Collection)
- 19 Credit Risk Factors (UCC, Legal, Payment Records . . .)

Matching IRS Data

- Prior Filing and Payment Information
- Dependent Variable: Balance Due Of At Least $5,000 in 4Q 2012

DISCLAIMER: The views and opinions presented in this presentation reflect those of the authors. They do not necessarily reflect the views or the official position of the Internal Revenue Service.
Both Data Sets

- After Validation, Prepared Data
  - Added Transformed Versions
    - Dollar & Count Variables
    - Square Root, Log, and Percent of Total Compensation
  - Binned Data
    - Credit Agency Defined Bins
  - Created Indicators
    - Specific Conditions
    - Changes Across Quarters
# Exploratory Data Analysis

<table>
<thead>
<tr>
<th>Credit Score Range</th>
<th>Credit Score Risk Class</th>
<th>1Q2012</th>
<th>2Q2012</th>
<th>3Q2012</th>
<th>4Q2012</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - 10</td>
<td>High</td>
<td>28.7%</td>
<td>28.7%</td>
<td>28.9%</td>
<td>28.7%</td>
<td>28.8%</td>
</tr>
<tr>
<td>11 - 25</td>
<td>High-Medium</td>
<td>29.2%</td>
<td>29.1%</td>
<td>28.6%</td>
<td>28.8%</td>
<td>28.9%</td>
</tr>
<tr>
<td>26 - 50</td>
<td>Medium</td>
<td>28.9%</td>
<td>28.9%</td>
<td>29.1%</td>
<td>29.2%</td>
<td>29.0%</td>
</tr>
<tr>
<td>51 - 75</td>
<td>Low-Medium</td>
<td>28.8%</td>
<td>29.0%</td>
<td>29.0%</td>
<td>28.9%</td>
<td>28.9%</td>
</tr>
<tr>
<td>76 - 100</td>
<td>Low</td>
<td>28.9%</td>
<td>28.7%</td>
<td>28.8%</td>
<td>29.0%</td>
<td>28.9%</td>
</tr>
</tbody>
</table>

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Variable Reduction

Each Data Set (Separately)

- **Factor Analysis**
  - Selected Most Correlated Variable From Each Factor
  - Internal Data: 60 Factors
  - External Data: 30 Factors

- **Initial Regressions**
  - Phase 1: Stepwise With 60 Internal Variables
  - Phase 2: Stepwise From Stage 1 & 30 External Variables

- Tested Dozens Of Additional Models Adding Additional Variables

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An additional 11 employers owing at least $5,000 have scores in the top decile.

<table>
<thead>
<tr>
<th>Model</th>
<th>AIC</th>
<th>SC</th>
<th>Somers’ D</th>
<th>AUC</th>
<th>Deviance</th>
<th>Top Decile Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>IRS Data Only</td>
<td>101,618</td>
<td>102,353</td>
<td>0.72</td>
<td>0.86</td>
<td>0.36</td>
<td>56.5%</td>
</tr>
</tbody>
</table>
### Phase II: Add External Data

<table>
<thead>
<tr>
<th>Model</th>
<th>AIC</th>
<th>SC</th>
<th>Somers’ D</th>
<th>AUC</th>
<th>Deviance</th>
<th>Top Decile Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>IRS Data Only</td>
<td>101,618</td>
<td>102,353</td>
<td>0.72</td>
<td>0.86</td>
<td>0.36</td>
<td>56.5%</td>
</tr>
<tr>
<td>Combined Data</td>
<td>101,608</td>
<td>102,383</td>
<td>0.72</td>
<td>0.86</td>
<td>0.37</td>
<td>56.5%</td>
</tr>
</tbody>
</table>

An additional 11 employers owing at least $5,000 have scores in the top decile.

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### Phase III: Reverse Prediction

<table>
<thead>
<tr>
<th>Model</th>
<th>AIC</th>
<th>SC</th>
<th>Somers’ D</th>
<th>AUC</th>
<th>Deviance</th>
<th>Top Decile Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worsening Credit Risk Class</td>
<td>113,706</td>
<td>113,840</td>
<td>0.34</td>
<td>0.67</td>
<td>0.50</td>
<td>22.8%</td>
</tr>
<tr>
<td>Worsening Finance Risk Class</td>
<td>172,586</td>
<td>172,752</td>
<td>0.32</td>
<td>0.66</td>
<td>0.77</td>
<td>17.3%</td>
</tr>
</tbody>
</table>

Used the 3rd Quarter 2012 Risk Class with IRS information to predict the 4th Quarter.
### Granger Causality Test

<table>
<thead>
<tr>
<th>Using This Data</th>
<th>To Predict</th>
<th>Chi-Square</th>
<th>Prob &gt; Chi-Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit Score</td>
<td>Payment Compliance</td>
<td>0.60</td>
<td>0.44</td>
</tr>
<tr>
<td>Financial Risk</td>
<td>Payment Compliance</td>
<td>2.17</td>
<td>0.14</td>
</tr>
<tr>
<td>Collection Prediction</td>
<td>Payment Compliance</td>
<td>0.72</td>
<td>0.40</td>
</tr>
</tbody>
</table>

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Conclusion

From This Project We Conclude:

- Available IRS Data Are Robust
  - We Can Build Strong Models From Internal Data

- External Credit Scores Add Little To These Models

- Reminder: This Applies Only To Employment Tax Prediction

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BETTER IDENTIFICATION OF POTENTIAL EMPLOYMENT TAX NONCOMPLIANCE USING CREDIT BUREAU DATA

IRS Research Conference
Internal Revenue Service
RAAS Taxpayer Behavior Lab

Saurabh Datta, Patrick Langetieg and Brenda Schafer

DISCLAIMER: The views and opinions presented in this paper reflect those of the authors. They do not necessarily reflect the views or the official position of the Internal Revenue Service
Research Objectives

- Demonstrate that matching a homogenous sample of employers with third-party short- and long-term credit bureau credit scores may proactively identify potential noncompliant employers
- Identify past behavior patterns and trends that may impact future behavior
- Show that the concurrent application of both the scores may inform risk policies
Sample Design

Phase I
- Detected cases were a rare event with realization rate of ~7%
- 32 Strata
- Analyzing employment tax noncompliance was not the sole purpose of this sample
- Sample Period: 2010Q4-2014Q4

Phase II
- Detected cases are over sampled to ~67% to understand and study potential noncompliance in greater detail
- 5 Strata
- Studying employment tax noncompliance is the sole objective of this sample
- Sample Period: 2012Q4-2016Q4
Data Structure

- Sample of 250,000 businesses
  - 160,627 matched with IRS’s administrative data
  - Reference Quarter = 2014Q4 (December)
  - Reviewed data from 8 prior quarters
  - 2 Credit Risk Scores (Short- and Long-Term)
  - 200+ Credit Risk Variables (Total Outstanding Balance, Lien Balance, Number of Legal Outstanding Issues, Accounts in Collection, No. of employees, etc.)
Definitions

- **Detected Noncompliant Employer**
  - An employer who received a first notice regarding potentially unpaid payroll taxes at some point during the eight quarters prior to 2014Q4 and whose case ultimately resolved in an assessment of unpaid payroll taxes
  - 67% of sample

- **Other Employer**
  - An employer who were not subjected to enforcement action during the eight quarters prior to 2014Q4
  - 33% of sample

- **Short Term Credit Score**
  - Predicts the likelihood of defaulting in the next 12 months on a credit obligation that has been past due for more than 91 days

- **Long Term Credit Score**
  - Predicts the probability of bankruptcy or the prospect of defaulting on 75 percent of the credit obligations that are more than 91 days past due
Lower deciles are associated with higher risk.

Recognition rate of Detected cases is only slightly better than the Other:
- 14 percent of the Detected cases are within the top two deciles of highest risk
- 13 percent of the Other cases are within the same range
Identification Rate of Detected and Other Cases based on Long-Term Credit Score (2014Q4)

- Clear separation between the risk profiles of Detected and Other cases
  - 33 percent of the Detected cases are within the top two deciles of highest risk
  - 26 percent of the Other cases are within the same range
Risk Classification Matrix

<table>
<thead>
<tr>
<th>Short-Term Risk</th>
<th>Long-Term Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Low</td>
<td>Stable Segment</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
</tr>
</tbody>
</table>

- **Medium Risk:**
  - Fulfilling short-term credit obligations
  - Lagging long-term credit payments

- **Slow Recovery:**
  - Experiencing difficulties with short-term credit obligations
  - Meeting long-term credit responsibilities

- **High Risk:**
  - Facing high possibility of financial crisis

Source: Experian, 2016; RAAS Taxpayer Behavior Lab, May 2017
## Risk Classification Matrix

### Detected Cases

<table>
<thead>
<tr>
<th>Short-Term Risk</th>
<th>Long-Term Risk</th>
<th>Stable Segment</th>
<th>Medium Risk</th>
<th>High Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low</td>
<td>(2014Q4:67.9%)</td>
<td>(2014Q4:13.5%)</td>
<td>(2014Q4:9.8%)</td>
</tr>
<tr>
<td></td>
<td>(2013Q4:67.4%)</td>
<td>(2013Q4:14.4%)</td>
<td>(2013Q4:9.8%)</td>
<td>(2013Q4:8.7%)</td>
</tr>
<tr>
<td></td>
<td>(2012Q4:69.8%)</td>
<td>(2012Q4:12.0%)</td>
<td>(2012Q4:9.9%)</td>
<td>(2012Q4:8.7%)</td>
</tr>
<tr>
<td>High</td>
<td>Slow Recovery</td>
<td>(2014Q4:8.8%)</td>
<td>(2014Q4:9.8%)</td>
<td>(2014Q4:9.5%)</td>
</tr>
<tr>
<td></td>
<td>(2013Q4:8.3%)</td>
<td>(2013Q4:9.9%)</td>
<td>(2012Q4:8.7%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2012Q4:9.5%)</td>
<td>(2012Q4:8.7%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Other Cases

<table>
<thead>
<tr>
<th>Short-Term Risk</th>
<th>Long-Term Risk</th>
<th>Stable Segment</th>
<th>Medium Risk</th>
<th>High Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low</td>
<td>(2014Q4:72.4%)</td>
<td>(2014Q4:10.0%)</td>
<td>(2014Q4:7.5%)</td>
</tr>
<tr>
<td></td>
<td>(2013Q4:71.9%)</td>
<td>(2013Q4:10.6%)</td>
<td>(2013Q4:7.9%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2012Q4:69.8%)</td>
<td>(2012Q4:12.0%)</td>
<td>(2012Q4:8.7%)</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>Slow Recovery</td>
<td>(2014Q4:10.1%)</td>
<td>(2014Q4:7.5%)</td>
<td>(2014Q4:9.5%)</td>
</tr>
<tr>
<td></td>
<td>(2013Q4:9.6%)</td>
<td>(2013Q4:7.9%)</td>
<td>(2012Q4:9.5%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2012Q4:9.5%)</td>
<td>(2012Q4:8.7%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- A larger percentage of the Detected cases are in the High Risk and Medium Risk segments
- The Detected category experienced decline in risk scores and Other cases an improvement in 2013 and 2014 compared to 2012
  - Biggest change in Detected cases is observed in the medium risk group
- Application of both scores simultaneously seems to provide better identification of potential payroll noncompliance
## Risk Classification Matrix

### Detected Cases Compared to Overall Detected Rate of 66.7 Percent

<table>
<thead>
<tr>
<th>Short-Term Risk</th>
<th>Long-Term Risk</th>
<th>2014Q4</th>
<th>2013Q4</th>
<th>2012Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Low</strong></td>
<td>Stable Segment</td>
<td>-1.4%</td>
<td>-1.5%</td>
<td>-1.3%</td>
</tr>
<tr>
<td></td>
<td>Medium Risk</td>
<td>6.3%</td>
<td>6.3%</td>
<td>5.6%</td>
</tr>
<tr>
<td><strong>High</strong></td>
<td>Slow Recovery</td>
<td>-3.0%</td>
<td>-3.3%</td>
<td>-4.3%</td>
</tr>
<tr>
<td></td>
<td>High Risk</td>
<td>5.5%</td>
<td>4.8%</td>
<td>3.9%</td>
</tr>
</tbody>
</table>

Note: Net percentage of Detected cases compared to overall rate of 66.7% is reported in parentheses.

- Joint application of both the scores may be able to identify potential cases prior to the observation period.
## Risk Classification Matrix

### Detected Cases with Legal Issues

<table>
<thead>
<tr>
<th>Short-Term Risk</th>
<th>Long-Term Risk</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>High</td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>Stable Segment</td>
<td>Medium Risk</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2014Q4: -2.8%)</td>
<td>(2014Q4: -4.1%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2013Q4: -5.6%)</td>
<td>(2013Q4: -5.8%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2012Q4: -9.1%)</td>
<td>(2012Q4: -10.5%)</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>Slow Recovery</td>
<td>High Risk</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2014Q4: 8.3%)</td>
<td>(2014Q4: 20.4%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2013Q4: 5.5%)</td>
<td>(2013Q4: 19.0%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2012Q4: 1.2%)</td>
<td>(2012Q4: 15.5%)</td>
<td></td>
</tr>
</tbody>
</table>

- **Note:** (1) Legal issues include tax liens at federal, state and local tax levels, bankruptcies, credit accounts in collection and UCC (Uniform Commercial Code) filings
- (2) The percentages in the parentheses represent the net percentage of Detected cases with legal issues in excess to the overall rate of 24.5%

---

When considering the presence of legal issues among Detected cases, the Slow Recovery and High Risk segments identify Detected cases better and earlier than the observation period.
Risk Classification Matrix

Detected Cases with Average Balance of $5,000 Across All Credit Lines

<table>
<thead>
<tr>
<th>Short-Term Risk</th>
<th>Long-Term Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Low</td>
<td>Stable Segment (2014Q4: 1.8%) (2013Q4: -0.7%) (2012Q4: -1.3%)</td>
</tr>
<tr>
<td>High</td>
<td>Slow Recovery (2014Q4: 14.8%) (2013Q4: 11.8%) (2012Q4: 10.9%)</td>
</tr>
</tbody>
</table>

Note: The percentages in the parentheses represents the net percentage of Detected cases with average balance of $5,000 in excess to the overall rate of 11.3%

- High credit balances may be indicative of risk among the Slow Recovery group
- Treatment Note:
  - Employers in the Slow Recovery category are attempting to improve their credit ratings. As a result, they may be more receptive to outreach and education on compliance and payment options than to default.
## Risk Classification Matrix

### Detected Cases among Businesses that are Less than 3 Years Old in 2012Q4

<table>
<thead>
<tr>
<th>Short-Term Risk</th>
<th>Long-Term Risk</th>
<th>2014Q4</th>
<th>2013Q4</th>
<th>2012Q4</th>
<th>2011Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low</td>
<td>Stable Segment</td>
<td>-1.7%</td>
<td>1.4%</td>
<td>4.2%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium Risk</td>
<td>7.5%</td>
<td>16.1%</td>
<td>21.5%</td>
</tr>
<tr>
<td>High</td>
<td>Slow Recovery</td>
<td>-1.2%</td>
<td>0.2%</td>
<td>1.6%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>High Risk</td>
<td>4.4%</td>
<td>9.4%</td>
<td>15.4%</td>
</tr>
</tbody>
</table>

Note: The percentages in the parentheses represents the net percentage of Detected cases with age of the business being less than 3 years in excess to the overall rate of 11.7%

- Newer businesses might be more likely to have a lower credit score
- Undercapitalized and market variability may make younger businesses more vulnerable to noncompliance
- A new business in the medium or high risk category may be at higher risk of default
Conclusions

- Preliminary evidence indicates that the combined credit bureau score method may be useful
  - Better identification and early detection of potential noncompliance
  - Improvements in detection rates for businesses in the Medium, High Risk and Slow recovery categories
  - Superior detection rates for different groupings within noncompliance categories

- Future research:
  - Study association between changes in credit score and Detected noncompliance
  - Further study the causality between the two credit scores and its impact on detecting future noncompliance
  - Development of a credit risk model (Markov Chain Transitional Matrix) to study the relationship between transition between credit categories and potential future noncompliance
Thank You

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Session 4
Creative Use of Non-Tax Data Sources

Discussion of

• Supplementing IRS Data with External Credit Report Data in Employment Tax Predictive Models (Curt Hopkins)

• Better Identification of Potential Employment Tax Noncompliance Using Credit Bureau Data (Saurabh Datta)

Adam Isen
(U.S. Treasury, Office of Tax Analysis)

IRS-TPC Research Conference
June 21, 2017
Estimating the Effects of Tax Reform on Compliance Burden

June 22, 2017
Daniel L. Berger, Eric Toder, Victoria Bryant, John Guyton and Patrick Langetieg
IRS – TPC Conference
Compliance costs are one part of the resource cost of taxation, these costs reflect the social cost imposed by taxes

Slemrod (2005)
- Compliance costs are predominately time and out of pocket expenses
- These costs include record keeping, preparation, learning about new forms / laws, lawyers, accountants, software etc.

What can be done to lower compliance costs?
TPC has recently built a version of the Individual Taxpayer Burden Model (ITBM) used by IRS RAAS into TPC’s microsimulation model.

IRS developed an adapted version of the model to work specifically with the SOI Public Use File (PUF).

This model allowed TPC to analyze baseline compliance costs and changes in compliance costs associated with reform plans.
Compliance Cost Model

- Rational taxpayer cost-minimization framework
  - Decreasing marginal costs with income
  - Time / money trade off based on productivity
- Calibrated to observe behavior
- Used in conjunction with tax calculator
- Compliance Cost Factors
  - Economic Activity
  - Tax preparation method
  - Complexity of taxpayer’s reporting requirements
Capturing Complexity

- Capture the degree to which reporting requirements demand additional recordkeeping
- Examples of the categories of increasing difficulty
  - **Low**: wages, interest, dividends
  - **Medium**: EITC, itemized deductions, business income
  - **High**: AMT credits, AMT taxable income, rental depreciation,
Adapted Burden Model

- Coefficients include preparation method, complexity categories, tax return line counts and modified positive income (MPI)
- The TPC adapted model is stratified by filing status
- Complexity category coefficients are slightly higher in adapted model
- The model was calibrated to meet aggregate totals, which may have implications for distributional estimates
Allocation of IRS Model Individual Taxpayer Compliance Cost, 2010

FIGURE 1
Composition of Discretionary Spending
Percent of Total

Source: Economic Report of the President, March 2013, Figure 3-10; https://obamawhitehouse.archives.gov/administration/eop/cea/economic-report-of-the-President/2013

www.taxpolicycenter.org
Allocation of TPC Model Individual Taxpayer Compliance Cost, 2017

FIGURE 2
Composition of Discretionary Spending
Percent of Total

- Other Taxes, 6.03%
- Wages, 22.18%
- Self-Employment Income, 12.59%
- Other Income, 12.59%
- Deductions, 28.58%
- Credits, 11.73%
- AMT, 6.30%

Source: Urban Brookings Tax Policy Center Microsimulation Model (version 0217-1)

www.taxpolicycenter.org
Baseline Compliance Burden Estimates

**TABLE 1**

<table>
<thead>
<tr>
<th>Expanded Cash Income Percentile</th>
<th>Percent Change in After Tax Income</th>
<th>Share of Total Federal Tax Change</th>
<th>Average Federal Tax Change ($)</th>
<th>Average Federal Tax Rate&lt;sup&gt;e&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Change (Percentage Points)</td>
</tr>
<tr>
<td>Lowest Quintile</td>
<td>-0.8</td>
<td>5.8</td>
<td>110</td>
<td>0.8</td>
</tr>
<tr>
<td>Middle Quintile</td>
<td>-0.7</td>
<td>14.8</td>
<td>410</td>
<td>0.6</td>
</tr>
<tr>
<td>Top Quintile</td>
<td>-0.8</td>
<td>49.4</td>
<td>1,910</td>
<td>0.6</td>
</tr>
<tr>
<td>Top 1 Percent</td>
<td>-0.6</td>
<td>10.7</td>
<td>8,780</td>
<td>0.4</td>
</tr>
<tr>
<td>All</td>
<td>-0.8</td>
<td>100.0</td>
<td>530</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Source: Urban Brookings Tax Policy Center Microsimulation Model (version 0217-1)
FIGURE 3
Average Dollar Value of Compliance Burden by ECI Quintile, 2017

FIGURE 4
Average Share of Pretax Income by ECI Quintile, 2017

Marcus et al. 2013

- Ways to limit compliance costs
  - Minimize / Eliminate reporting where information of little use to tax policy or administration
  - Consider whether the policy outweighs the cost of compliance for taxpayers
  - Target Drivers of taxpayer compliance

- TPC’s reform options focus on the third mechanism of lowering compliance costs
Reform Option 1

- Revenue neutral repeal of itemized deductions by proportionally increasing the standard

**TABLE 2**
Change in tax and compliance cost as a share of pretax income, 2017

<table>
<thead>
<tr>
<th>Expanded cash income percentile</th>
<th>Compliance Cost</th>
<th>Tax &amp; Compliance Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lowest Quintile</td>
<td>-0.2</td>
<td>-0.7</td>
</tr>
<tr>
<td>Middle Quintile</td>
<td>-0.2</td>
<td>-1.7</td>
</tr>
<tr>
<td>Top Quintile</td>
<td>-0.2</td>
<td>1.0</td>
</tr>
<tr>
<td>Top 1 Percent</td>
<td>-0.2</td>
<td>2.3</td>
</tr>
<tr>
<td>All</td>
<td>-0.2</td>
<td>-0.2</td>
</tr>
</tbody>
</table>

Source: Urban Brookings Tax Policy Center Microsimulation Model (version 0217-1)
Reform Option 2

- Revenue neutral repeal of itemized deductions except the mortgage interest and charitable giving deductions by proportionally increasing the standard deduction

### TABLE 3
Change in tax and compliance cost as a share of pretax income, 2017

<table>
<thead>
<tr>
<th>Expanded cash income percentile</th>
<th>Compliance Cost</th>
<th>Tax &amp; Compliance Cost</th>
</tr>
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<tbody>
<tr>
<td>Lowest Quintile</td>
<td>-0.2</td>
<td>-0.7</td>
</tr>
<tr>
<td>Middle Quintile</td>
<td>-0.2</td>
<td>-1.3</td>
</tr>
<tr>
<td>Top Quintile</td>
<td>-0.2</td>
<td>0.7</td>
</tr>
<tr>
<td>Top 1 Percent</td>
<td>-0.2</td>
<td>1.5</td>
</tr>
<tr>
<td>All</td>
<td>-0.2</td>
<td>-0.2</td>
</tr>
</tbody>
</table>

Source: Urban Brookings Tax Policy Center Microsimulation Model (version 0217-1)
Reform Option 3

- Revenue neutral repeal of the Alternative Minimum Tax by pairing down the state and local tax deduction

**TABLE 4**

<table>
<thead>
<tr>
<th>Expanded cash income percentile</th>
<th>Compliance Cost</th>
<th>Tax &amp; Compliance Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lowest Quintile</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Second Quintile</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Middle Quintile</td>
<td>0.0</td>
<td>0.1</td>
</tr>
<tr>
<td>Fourth Quintile</td>
<td>0.0</td>
<td>0.1</td>
</tr>
<tr>
<td>Top Quintile</td>
<td>-0.1</td>
<td>-0.2</td>
</tr>
<tr>
<td>All</td>
<td>0.0</td>
<td>-0.1</td>
</tr>
</tbody>
</table>

**Addendum**

<table>
<thead>
<tr>
<th>Percentile</th>
<th>Compliance Cost</th>
<th>Tax &amp; Compliance Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>80-90</td>
<td>0.0</td>
<td>0.2</td>
</tr>
<tr>
<td>90-95</td>
<td>0.0</td>
<td>0.1</td>
</tr>
<tr>
<td>95-99</td>
<td>-0.2</td>
<td>-0.7</td>
</tr>
<tr>
<td>Top 1 Percent</td>
<td>-0.1</td>
<td>-0.2</td>
</tr>
<tr>
<td>Top 0.1 Percent</td>
<td>0.0</td>
<td>-0.2</td>
</tr>
</tbody>
</table>
TPC estimates that individual taxpayer compliance costs for 2017 were $92 billion or an average of $530 per tax filer.

While compliance costs increase with Expanded Cash Income (ECI), the lowest ECI quintile’s costs are the highest as a share of pre-tax income.

Simplifying the tax can lead to lower burden costs, and mitigate costs for taxpayers that might otherwise see tax increases.
Next Steps

- IRS will continue to work with TPC to calibrate and test the PUF model to better align with the IRS full model results
- IRS will provide public documentation of the burden model to accompany the PUF
THANK YOU

For more information please contact:

Daniel Berger
dberger@urban.org

View other studies at
www.taxpolicycenter.org
Counting Elusive Nonfilers
Using IRS Rather Than Census Data

Pat Langetieg, Mark Payne, and Alan Plumley
IRS Research, Applied Analytics, and Statistics:
Knowledge Development & Application Division

IRS-TPC Research Conference
June 21, 2017
Voluntary Filing Rate (VFR) Estimation

The VFR is defined as:

\[ VFR = \frac{\text{Number of Required Returns Filed on Time}}{\text{Total Number of Returns Required to be Filed}} \]

Previous Census Method:

- Numerator estimated from IRS population data containing all filed returns.
- Income imputed to CPS-ASEC to correct understatement of income in survey.
- But in work on the nonfiling tax gap we discovered that total number of required taxpayers in the population should be substantially higher (~11 million).
## Limitations of Census Data for Estimating Required Returns

Thousands of Returns in VFR Components Estimated by Different Methods, TY 2010

<table>
<thead>
<tr>
<th></th>
<th>Old VFR</th>
<th>Nonfiler Tax Gap</th>
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<tbody>
<tr>
<td></td>
<td><strong>Admin</strong></td>
<td><strong>Census Matched</strong></td>
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<td><strong>Numerator</strong></td>
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<td><strong>Denominator</strong></td>
<td>(total required returns)</td>
<td>122,200</td>
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<tr>
<td><strong>Difference</strong></td>
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<td>6,300</td>
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<td><strong>Numerator/Denominator</strong></td>
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Efforts to Correct CPS-Based Underestimates of Required Population

- Base total income on the 1040 amount when available; OR
- Backend imputation of gross income calibrated to totals in IRS data

Result not satisfactory. Significantly lower VFR estimates for Tax Year 2007 than subsequent years. This contradicts expectations and evidence from IRS administrative data that because of stimulus credits the VFR should be higher in this year.
IRS Administrative Method

- **Timely and late required filers:**
  - Determine whether timely or late and whether required or not based on gross income and net self employment thresholds.
  - For consistent series, taxpayers filing more than two years after the end of tax year are treated as not-filers.

- **Not-filers (all others):**
  - On information return but not on tax return (by two year cutoff)
  - Impute net self-employment income (based on $ reported among filers).
  - Gross up net self employment income < $433.
  - Randomly assign individuals to tax units based on CPS.
  - Determine whether required to file – same as timely and late filers.
IRS population is fairly close to US Census population estimates.
6.5% (~8 million) larger required population, results in VFR estimate that is about 5% lower than CPS method.

Note: The 2015 IRS Administrative Data-based VFR is provisional.
The late-filer portion of nonfilers has declined in last few years, presumably due in part due to reduced nonfiler enforcement.
Returns with refunds make up large share of returns filed in the first months after deadline but smaller share later.

Count of Balance Due and Refund Late Returns by Degree of Lateness, TY 2012

- Refund = 3.5 Million
  Bal Due = 1.6 Million
- Refund = 0.5 Million
  Bal Due = 0.6 Million

Oct. 15, 2013: Filing extension deadline
Dec 31, 2014: Subsequent late filers treated as not-filers in VFR

Weeks from Original Filing Deadline

- Refund
- Balance Due
Most non-enforced late returns are filed within two years.

Returns secured through enforcement peak about one year after the filing deadline.

Not a large number of returns in third and fourth years after end of tax year so no significant loss in accuracy.
Characteristics of Nonfilers and Drivers of Nonfiling

- Since it uses the same data source for the numerator and denominator, the IRS administrative data method facilitates examination of the causes of VFR fluctuations.
- In addition, this method can facilitate learning about drivers of nonfiling.
- Imprecise at the micro level because of SE imputation and family unit imputations. But, limitations also exist with IRS-Census matched data.
- Could analyze filing behavior without SE imputations and without imputed tax units (i.e., assume all taxpayers are single) to test sensitivity of results to different assumptions.
The VFR is about 1.6% lower with SE income imputation, but the trend with and without is similar.
The VFR is stable and high for those owed a refund; much lower and less stable for those with a balance due.
The VFR is much higher for those whose earned income is limited to wages and much lower for those with only SE income.
This is true even when SE imputation is removed, though difference in VFR is less.
VFR is much higher for those who filed timely in the previous year.
VFR (for given gross income bin) increases as gross income increases relative to the filing threshold.
VFR Married Taxpayers (<65 Years Old) by Gross Income, TY 2014

Similar pattern for married taxpayers

Married Threshold = $20,300
Lower VFR for middle age taxpayers and later ages; unclear which underlying variables lead to dip in filing.
Pattern more pronounced for single taxpayers
But, less pronounced for married taxpayers
Distribution of gross income among nonfilers has a long tail.

Late filer and timely filer average gross income higher than for not-filers.
Late-filed and timely filed returns also have higher tax liability than returns that are not filed within two years of end of tax year.
- Larger share of refund nonfiler returns are late filers
- Larger share of balance due nonfiler returns are not-filers
Benefits of This Research

- More accurate measure of the VFR
- Better understanding of the gaps in income reported in the CPS
- Technique developed to adjust for rounding of income responses in the CPS
- Improved ability to explore factors affecting fluctuations in the VFR and to gain insights on drivers of nonfiling
Future Work

- Impute corrected (single) filing status to some of those incorrectly claiming Head of Household status
- Improve imputation of tax units by drawing on information from prior year returns and SSA data
- Further explore the use of expanded Census-IRS matched data to develop alternative VFR measure and to examine drivers of nonfiling
- Explore use of IRS administrative data in multivariate analysis of drivers of nonfiling
Estimating the Effects of Tax Reform on Compliance Burdens
&
Counting Elusive Nonfilers

Discussant: Emily Y. Lin
Office of Tax Analysis
U.S. Department of the Treasury

7th Annual IRS-TPC Joint Research Conference on Tax Administration
June 21, 2017
Estimating the Effects of Tax Reform on Compliance Burdens

- Understanding the sources of compliance burdens and establishing method to evaluate taxpayer compliance costs provide important guidance on tax administration and simplification.

- IRS Individual Taxpayer Burden Model (ITBM) is built on survey data and simulated off internal tax return files while TPC has to rely on Public Use Files (PUFs).
  - PUFs do not contain the same level of accuracy and detail about certain types of returns or tax fields as those available on the administrative data.

- Restructure the burden analysis to base the cost estimates and equations on tax fields available on PUFs.
Distribution of Estimated Burden Cost
Total Burden Cost ($), 2007

Percentile of the Burden Distribution

IRS

TPC

$
## Composition of Burden Cost by Income and Tax Item

**Percent of Total Burden Cost, 2017**

<table>
<thead>
<tr>
<th>Income Category</th>
<th>TPC</th>
<th>IRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Other Income</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>AMT</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>Credits</td>
<td>12</td>
<td>14</td>
</tr>
<tr>
<td>Deductions</td>
<td>29</td>
<td>25</td>
</tr>
<tr>
<td>Self-Employment Income</td>
<td>13</td>
<td>19</td>
</tr>
<tr>
<td>All Other Non-Wage Income</td>
<td>13</td>
<td>18</td>
</tr>
<tr>
<td>Wages</td>
<td>22</td>
<td>18</td>
</tr>
</tbody>
</table>
Issues to Consider

• **Restore the distribution of complexity categories**
  – Impute key missing fields to the model based on the known distribution of the tax variables in the IRS data.

• **Preparation methods: Endogenous?**

• **Change the pre-determined complexity level associated with each line item with proposals**
  – Proposals that do not involve eliminating a line item but greatly simplify the provision.

• **Compliance cost of filing; the cost of time vs. out-of-pocket expenses for each line item**
  – Distinguish the cost of record keeping from the cost associated with claiming a deduction/credit or filing a tax return.
Counting Nonfilers

- **Two components:**
  1. How many returns are **required to be filed**?
  2. How many of the required returns are **filed on time**?
    - **Difference** = Implied Nonfilers (including late filers and not-filers)
    - **Ratio**, $\frac{(2)}{(1)} = \text{Voluntary Filing Rate (VFR)}$

- **One can use either the CPS or IRS administrative data** to estimate these two components. Each data source has its own disadvantages and advantages.
  - Impute understated or missing income items.
  - Impute filing status, spouse income, number of dependents, and, to a lesser extent, underreported income.

- **Another approach:** Use CPS data for the first component and IRS for the second component.
### Thousands of Returns in VFR Components Estimated by Different Methods, Tax Year 2010

<table>
<thead>
<tr>
<th></th>
<th>VFR Method</th>
<th>Census Method</th>
<th>Administrative Data Method</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Numerator (required returns filed on time)</strong></td>
<td>115,900</td>
<td>105,001</td>
<td>115,900</td>
</tr>
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<td><strong>Denominator (total required returns)</strong></td>
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<td>119,967</td>
<td>130,787</td>
</tr>
<tr>
<td><strong>Difference (implied number of nonfilers)</strong></td>
<td>6,300</td>
<td>14,966</td>
<td>14,937</td>
</tr>
<tr>
<td><strong>Numerator/Denominator (Implied VFR)</strong></td>
<td>94.8%</td>
<td>87.5%</td>
<td>88.6%</td>
</tr>
</tbody>
</table>
Figure 1. IRS Administrative Data Population vs. Decennial Census Population by Age, TY2010

- Fewer young children
- Fewer working age individuals
- More elderly
Issues to Consider

- **Insufficient income imputation to the CPS?**
  - Population difference between the CPS and Administrative Data
    - CPS sample consists of U.S. households. Excludes people in institutions and Americans living abroad. May include non-residents who do not have a filing requirement.
    - May be problematic to draw required returns and timely filed returns from different data sources.

- **Assign spouses and dependents to not-filers in the Administrative Data**
  - Do spouses have income (i.e., are spouses drawn from the third-party information database)?
    - Overestimate the income of married not-filers?
    - Middle-age spouses who do not have third-party information returns?
  - Use additional information returns, e.g., Form 1095 of health insurance marketplace statement to identify dependents?

- **Low VFRs for middle age taxpayers, relative to the VFRs of younger and older taxpayers.**
  - Consider factors (e.g., income composition, spousal income imputation, SE income imputation, etc.) for the pattern.
  - Check the presence of SE income against survey data.

- **Estimate trend of the nonfiling tax gap based on consistent methodology.**
# Session 4. Creative Use of Non-Tax Data Sources

**Moderator:** Emily Lin  
*U.S. Treasury Office of Tax Analysis*

<table>
<thead>
<tr>
<th>Topic</th>
<th>Presenter</th>
<th>Affiliation</th>
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<tbody>
<tr>
<td>Supplementing IRS Data with External Credit Report Data in Employment Tax Predictive Models</td>
<td>Curt Hopkins</td>
<td>IRS, SB/SE</td>
</tr>
<tr>
<td>Better Identification of Potential Employment Tax Noncompliance Using Credit Bureau Data</td>
<td>Saurabh Datta</td>
<td>IRS, RAAS</td>
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<tr>
<td>Estimating the Effects of Tax Reform on Compliance Burdens</td>
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**Discussant:**  
Adam Isen and Emily Lin  
*U.S. Treasury Office of Tax Analysis*