Research, Applied Analytics, and Statistics

TAX POLICY CENTER
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# Session 4. Creative Use of Non-Tax Data Sources

| | |
|---|---|
| **Moderator:** | ***Emily Lin***<br>*U.S. Treasury Office of Tax Analysis* |
| **Supplementing IRS Data with External Credit Report Data in Employment Tax Predictive Models** | ***Curt Hopkins***<br>*IRS, SB/SE* |
| **Better Identification of Potential Employment Tax Noncompliance Using Credit Bureau Data** | ***Saurabh Datta***<br>*IRS, RAAS* |
| **Estimating the Effects of Tax Reform on Compliance Burdens** | ***Daniel Berger***<br>*Tax Policy Center* |
| **Counting Elusive Nonfilers Using IRS Rather Than Census Data** | ***Mark Payne***<br>*IRS, RAAS* |
| **Discussant:** | ***Adam Isen*** *and* ***Emily Lin***<br>*U.S. Treasury Office of Tax Analysis* |

IRS

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

# Data Preparation

## 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

| | | Percent with an Unpaid Balance > $1,000 | | | | |
|---|---|---|---|---|---|---|
| **Credit Score Range** | **Credit Score Risk Class** | **1Q2012** | **2Q2012** | **3Q2012** | **4Q2012** | **Average** |
| 1 - 10 | High | 28.7% | 28.7% | 28.9% | 28.7% | 28.8% |
| 11 - 25 | High-Medium | 29.2% | 29.1% | 28.6% | 28.8% | 28.9% |
| 26 - 50 | Medium | 28.9% | 28.9% | 29.1% | 29.2% | 29.0% |
| 51 - 75 | Low-Medium | 28.8% | 29.0% | 29.0% | 28.9% | 28.9% |
| 76 -100 | Low | 28.9% | 28.7% | 28.8% | 29.0% | 28.9% |

# 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

# Phase II: Add External Data

| Model | AIC | SC | Somers' D | AUC | Deviance | Top Decile Percent |
|---|---|---|---|---|---|---|
| **IRS Data Only** | 101,618 | 102,353 | 0.72 | 0.86 | 0.36 | 56.5% |

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

# Phase II: Add External Data

| Model | AIC | SC | Somers' D | AUC | Deviance | Top Decile Percent |
|---|---|---|---|---|---|---|
| **IRS Data Only** | 101,618 | 102,353 | 0.72 | 0.86 | 0.36 | 56.5% |
| **Combined Data** | 101,608 | 102,383 | 0.72 | 0.86 | 0.37 | 56.5% |

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

# Phase III: Reverse Prediction

| Model | AIC | SC | Somers' D | AUC | Deviance | Top Decile Percent |
|---|---|---|---|---|---|---|
| **Worsening Credit Risk Class** | 113,706 | 113,840 | 0.34 | 0.67 | 0.50 | 22.8% |
| **Worsening Finance Risk Class** | 172,586 | 172,752 | 0.32 | 0.66 | 0.77 | 17.3% |

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

# Granger Causality Test

| Using This Data | To Predict | Chi-Square | Prob > Chi-Square |
|---|---|---|---|
| **Credit Score** | Payment Compliance | 0.60 | 0.44 |
| **Financial Risk** | Payment Compliance | 2.17 | 0.14 |
| **Collection Prediction** | Payment Compliance | 0.72 | 0.40 |

# 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

June 21, 2017

# BETTER IDENTIFICATION OF POTENTIAL EMPLOYMENT TAX NONCOMPLIANCE USING CREDIT BUREAU DATA

## IRS Research Conference

### Internal Revenue Service

### RAAS Taxpayer Behavior Lab

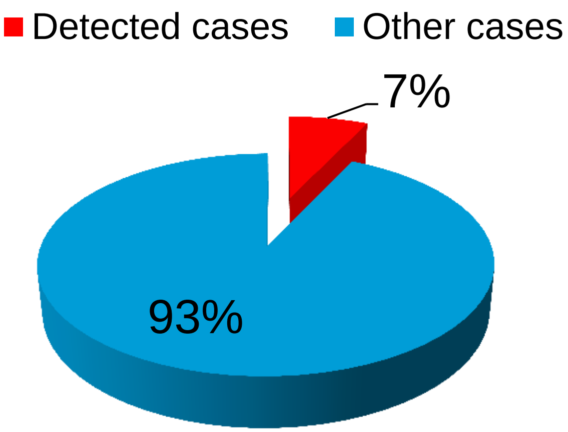
Saurabh Datta, Patrick Langetieg and Brenda Schafer

# 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

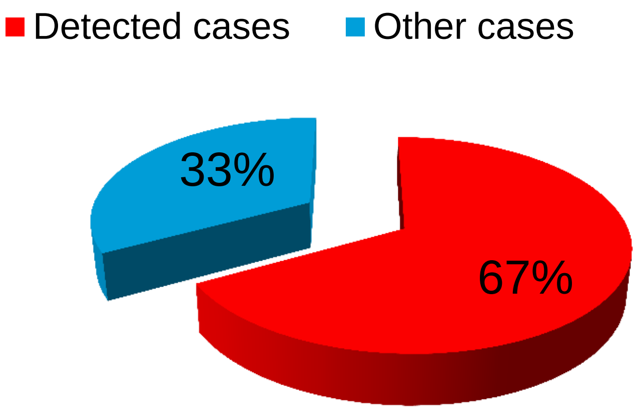
# Sample Design

## 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

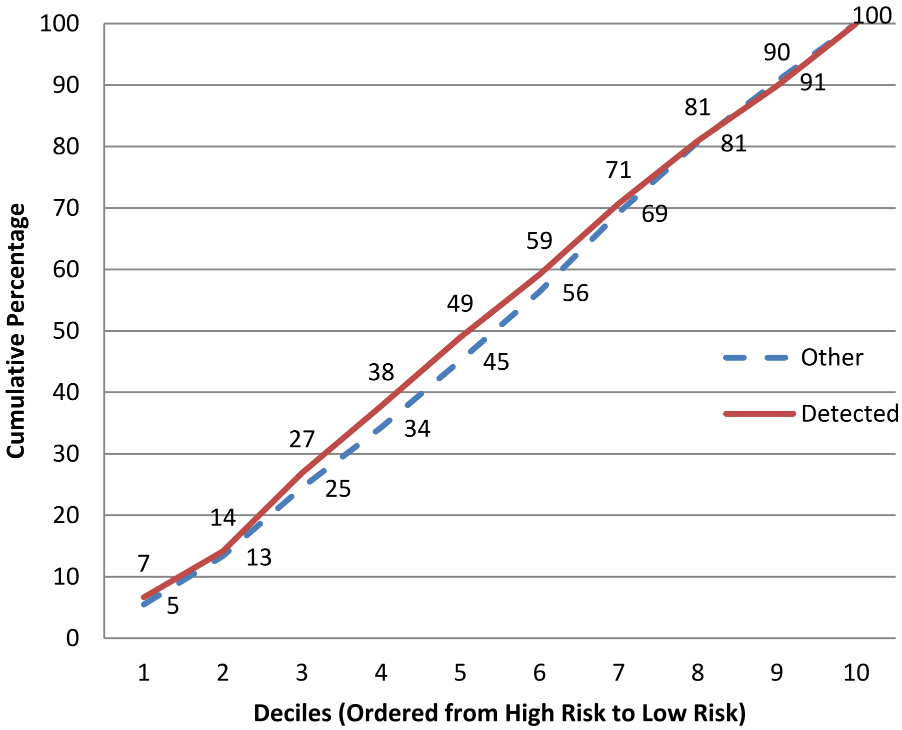
# Data Structure

- 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

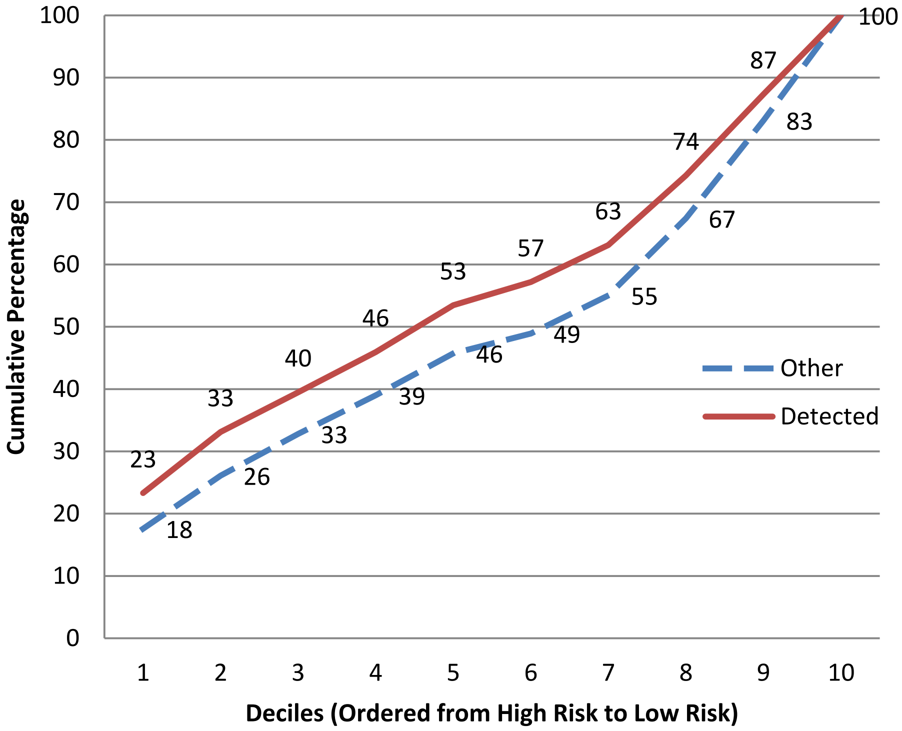
- Detected Noncompliant Employer
  - An employer who received a first notice regarding potentially unpaid payroll taxes at some point during the eight quarters prior to 2014Q4 and whose case ultimately resolved in an assessment of unpaid payroll taxes
  - 67% of sample
- Other Employer
  - An employer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

# Identification Rate of Detected and Other Cases based on Short-Term Credit Score (2014Q4)




- 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

| Short-Term Risk | Long-Term Risk | |
|---|---|---|
| | Low | High |
| Low | Stable Segment | Medium Risk |
| High | Slow Recovery | High Risk |

Source: Experian, 2016; RAAS Taxpayer Behavior Lab, May 2017

**Combination of Two Risk Scores**

- **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

# Risk Classification Matrix

## Detected Cases

| Short-Term Risk | Long-Term Risk | |
|---|---|---|
| | Low | High |
| Low | Stable Segment (2014Q4:67.9%) (2013Q4:67.4%) (2012Q4:69.8%) | Medium Risk (2014Q4:13.5%) (2013Q4:14.4%) (2012Q4:12.0%) |
| High | Slow Recovery (2014Q4:8.8%) (2013Q4:8.3%) (2012Q4:9.5%) | High Risk (2014Q4:9.8%) (2013Q4:9.9%) (2012Q4:8.7%) |

## Other Cases

| Short-Term Risk | Long-Term Risk | |
|---|---|---|
| | Low | High |
| Low | Stable Segment (2014Q4:72.4%) (2013Q4:71.9%) (2012Q4:69.8%) | Medium Risk (2014Q4:10.0%) (2013Q4:10.6%) (2012Q4:12.0%) |
| High | Slow Recovery (2014Q4:10.1%) (2013Q4:9.6%) (2012Q4:9.5%) | High Risk (2014Q4:7.5%) (2013Q4:7.9%) (2012Q4:8.7%) |

- 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

| Short-Term Risk | Long-Term Risk | |
|---|---|---|
| | Low | High |
| Low | Stable Segment (2014Q4: -1.4%) (2013Q4: -1.5%) (2012Q4: -1.3%) | Medium Risk (2014Q4: 6.3%) (2013Q4: 6.3%) (2012Q4: 5.6%) |
| High | Slow Recovery (2014Q4: -3.0%) (2013Q4: -3.3%) (2012Q4: -4.3%) | High Risk (2014Q4: 5.5%) (2013Q4: 4.8%) (2012Q4: 3.9%) |

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

| Short-Term Risk | Long-Term Risk: Low | Long-Term Risk: High |
|---|---|---|
| Low | Stable Segment (2014Q4: -2.8%) (2013Q4: -5.6%) (2012Q4: -9.1%) | Medium Risk (2014Q4: -4.1%) (2013Q4: -5.8%) (2012Q4: -10.5%) |
| High | Slow Recovery (2014Q4: 8.3%) (2013Q4: 5.5%) (2012Q4: 1.2%) | High Risk (2014Q4: 20.4%) (2013Q4: 19.0%) (2012Q4: 15.5%) |

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 represents 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

| Short-Term Risk | Long-Term Risk | |
|---|---|---|
| | Low | High |
| Low | Stable Segment (2014Q4: 1.8%) (2013Q4: -0.7%) (2012Q4: -1.3%) | Medium Risk (2014Q4: -11.3%) (2013Q4: -11.3%) (2012Q4: -11.3%) |
| High | Slow Recovery (2014Q4: 14.8%) (2013Q4: 11.8%) (2012Q4: 10.9%) | High Risk (2014Q4: -3.4%) (2013Q4: -3.6%) (2012Q4: -3.8%) |

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 my 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

| Short-Term Risk | Long-Term Risk | |
|---|---|---|
| | Low | High |
| Low | Stable Segment (2014Q4: -1.7%) (2013Q4: 1.4%) (2012Q4: 4.2%) | Medium Risk (2014Q4: 7.5%) (2013Q4: 16.1%) (2012Q4: 21.5%) |
| High | Slow Recovery (2014Q4: -1.2%) (2013Q4: 0.2%) (2012Q4: 1.6%) | High Risk (2014Q4: 4.4%) (2013Q4: 9.4%) (2012Q4: 15.4%) |

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

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

# 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

TPC TAX POLICY CENTER
URBAN INSTITUTE & BROOKINGS INSTITUTION

# Introduction

- 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?

# Model Overview

- 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

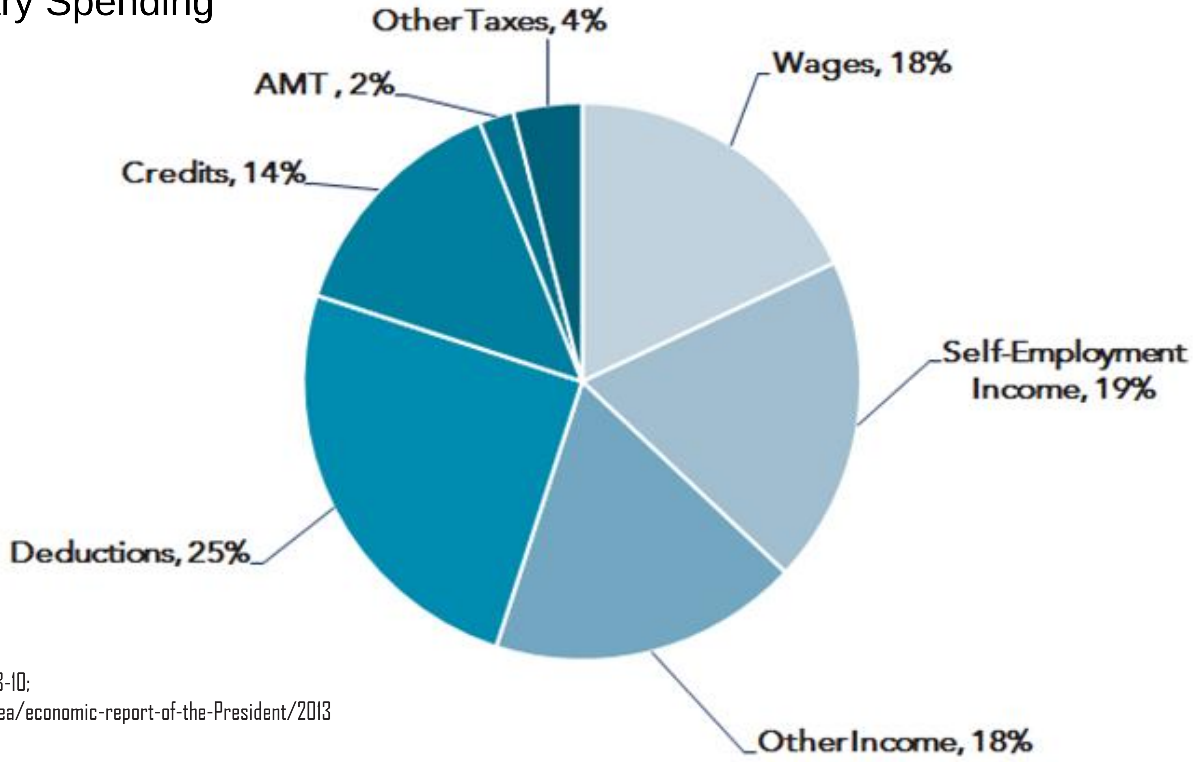
- Coefficients include preparation method, complexity categories, tax return line counts and modified positive income (MPI)
- The TPC adapted model is stratified by filing status
- Complexity category coefficients are slightly higher in adapted model
- The model was calibrated to meet aggregate totals, 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



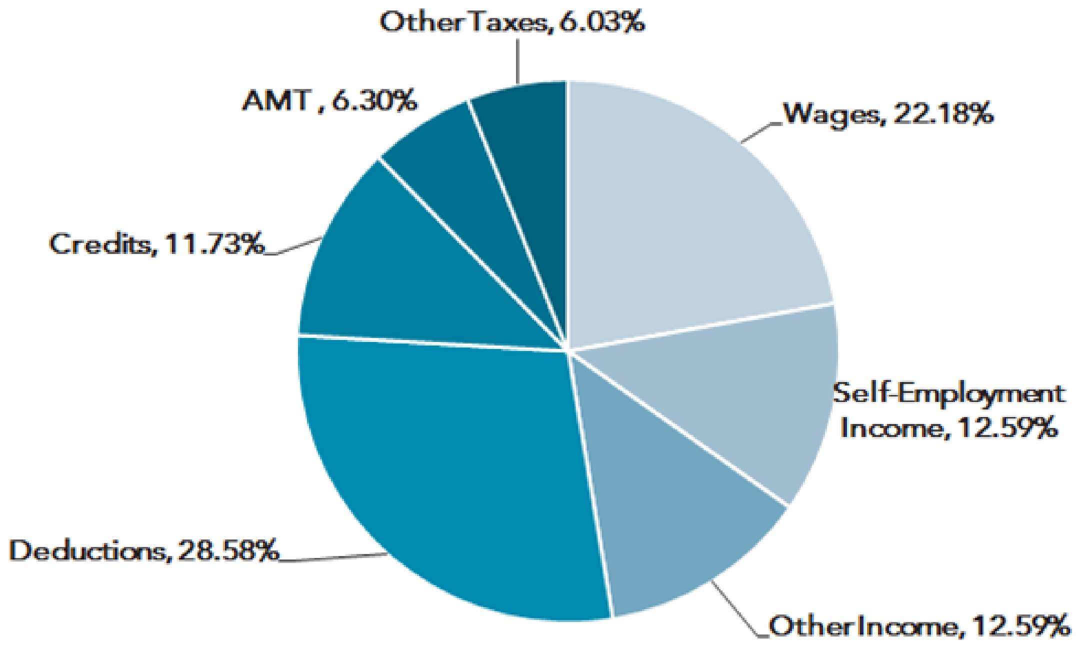

Source: Economic Report of the President, March 2013, Figure 3-10; https://obamawhitehouse.archives.gov/administration/eop/cea/economic-report-of-the-President/2013

# Allocation of TPC Model Individual Taxpayer Compliance Cost, 2017

FIGURE 2

## Composition of Discretionary Spending

Percent of Total




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

# Baseline Compliance Burden Estimates

TABLE 1

Distribution of Compliance Cost by Expanded Cash Income Percentile, 2017

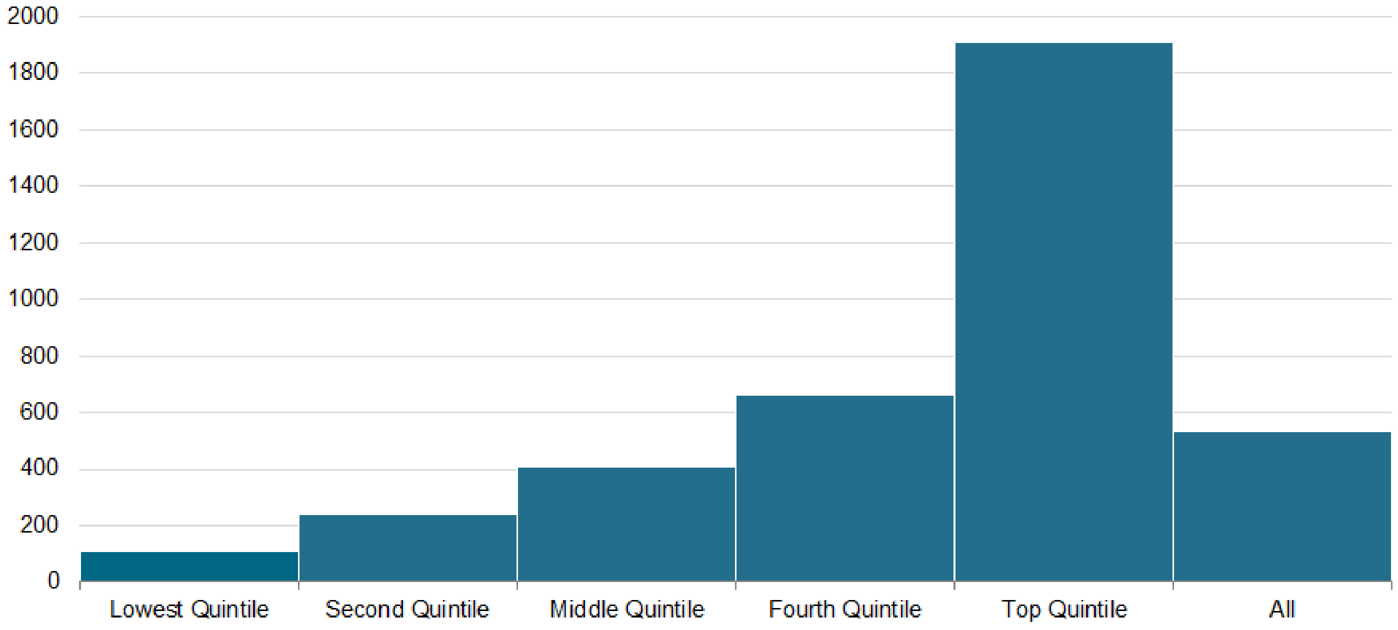
| Expanded Cash Income Percentile | Percent Change in After Tax Income | Share of Total Federal Tax Change | Average Federal Tax Change ($) | Average Federal Tax Rate[e] | |
|---|---|---|---|---|---|
| | | | | Change (Percentage Points) | Under the Proposal |
| **Lowest Quintile** | -0.8 | 5.8 | 110 | 0.8 | 5.0 |
| **Middle Quintile** | -0.7 | 14.8 | 410 | 0.6 | 14.6 |
| **Top Quintile** | -0.8 | 49.4 | 1,910 | 0.6 | 26.3 |
| **Top 1 Percent** | -0.6 | 10.7 | 8,780 | 0.4 | 33.3 |
| **All** | -0.8 | 100.0 | 530 | 0.6 | 20.6 |

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

# Compliance Cost in Dollars, 2017

FIGURE 3

Average Dollar Value of Compliance Burden by ECI Quintile, 2017

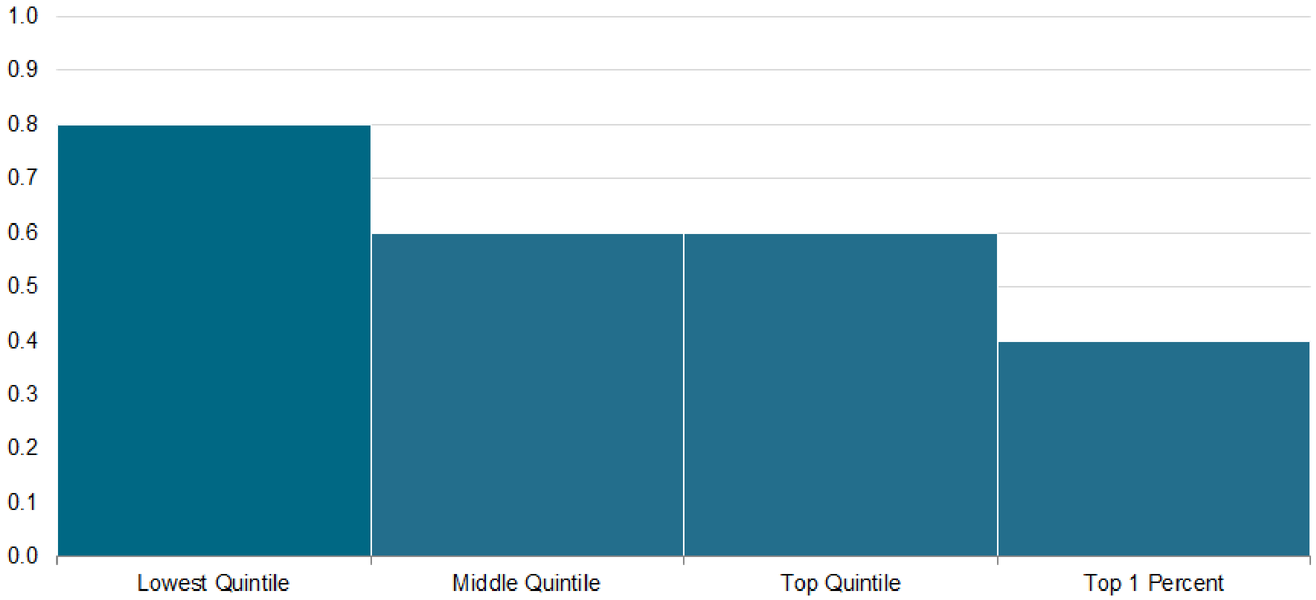



**Source:** Urban-Brookings Tax Policy Center Microsimulation Model (version 0217-1).

# Compliance Cost Share of Pretax Income,

FIGURE 4

Average Share of Pretax Income by ECI Quintle, 2017




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

# Reducing Compliance Costs

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 deduction

TABLE 2

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

| Expanded cash income percentile | Compliance Cost | Tax & Compliance Cost |
|---|---|---|
| Lowest Quintile | -0.2 | -0.7 |
| Middle Quintile | -0.2 | -1.7 |
| Top Quintile | -0.2 | 1.0 |
| Top 1 Percent | -0.2 | 2.3 |
| All | -0.2 | -0.2 |

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

| Expanded cash income percentile | Compliance Cost | Tax & Compliance Cost |
|---|---|---|
| Lowest Quintile | -0.2 | -0.7 |
| Middle Quintile | -0.2 | -1.3 |
| Top Quintile | -0.2 | 0.7 |
| Top 1 Percent | -0.2 | 1.5 |
| All | -0.2 | -0.2 |

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

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

| Expanded cash income percentile | Compliance Cost | Tax & Compliance Cost |
|---|---|---|
| Lowest Quintile | 0.0 | 0.0 |
| Second Quintile | 0.0 | 0.0 |
| Middle Quintile | 0.0 | 0.1 |
| Fourth Quintile | 0.0 | 0.1 |
| Top Quintile | -0.1 | -0.2 |
| All | 0.0 | -0.1 |
| | | |
| Addendum | | |
| 80-90 | 0.0 | 0.2 |
| 90-95 | 0.0 | 0.1 |
| 95-99 | -0.2 | -0.7 |
| Top 1 Percent | -0.1 | -0.2 |
| Top 0.1 Percent | 0.0 | -0.2 |

# Estimation Takeaways

- 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
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View other studies at
www.taxpolicycenter.org

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# 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:

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

**Previous Census Method:**

- Numerator estimated from IRS population data containing all filed returns.
- Denominator estimated from the Census Bureau's *Current Population Survey, Annual Social and Economic Supplement* (CPS-ASEC).
- 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

| | Old VFR | Nonfiler Tax Gap | |
|---|---|---|---|
| | $\frac{Admin}{Census}$ | $\frac{Census\ Matched}{Census\ Matched}$ | $\frac{Admin}{Admin}$ |
| **Numerator** (required returns filed on time) | **115,900** | | |
| **Denominator** (total required returns) | **122,200** | | |
| **Difference** (implied number of nonfilers) | **6,300** | | |
| **Numerator/Denominator** (implied VFR) | **94.8%** | | |

# Limitations of Census Data for Estimating Required Returns

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

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|---|---|---|---|
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| **Numerator** (required returns filed on time) | 115,900 | 105,001 | |
| **Denominator** (total required returns) | 122,200 | 119,967 | |
| **Difference** (implied number of nonfilers) | 6,300 | 14,966 | |
| **Numerator/Denominator** (implied VFR) | 94.8% | 87.5% | |

# Limitations of Census Data for Estimating Required Returns

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

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| **Numerator** (required returns filed on time) | **115,900** | **105,001** | **115,900** |
| **Denominator** (total required returns) | **122,200** | **119,967** | **130,787** |
| **Difference** (implied number of nonfilers) | **6,300** | **14,966** | **14,937** |
| **Numerator/Denominator** (implied VFR) | **94.8%** | **87.5%** | **88.6%** |

# Limitations of Census Data for Estimating Required Returns

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

| | Old VFR | Nonfiler Tax Gap | |
|---|---|---|---|
| | *Admin / Census* | *Census Matched / Census Matched* | *Admin / Admin* |
| **Numerator** (required returns filed on time) | 115,900 | 105,001 | 115,900 |
| **Denominator** (total required returns) | 122,200 | 119,967 | 130,787 |
| **Difference** (implied number of nonfilers) | 6,300 | 14,966 | 14,937 |
| **Numerator/Denominator** (implied VFR) | 94.8% | 87.5% | 88.6% |

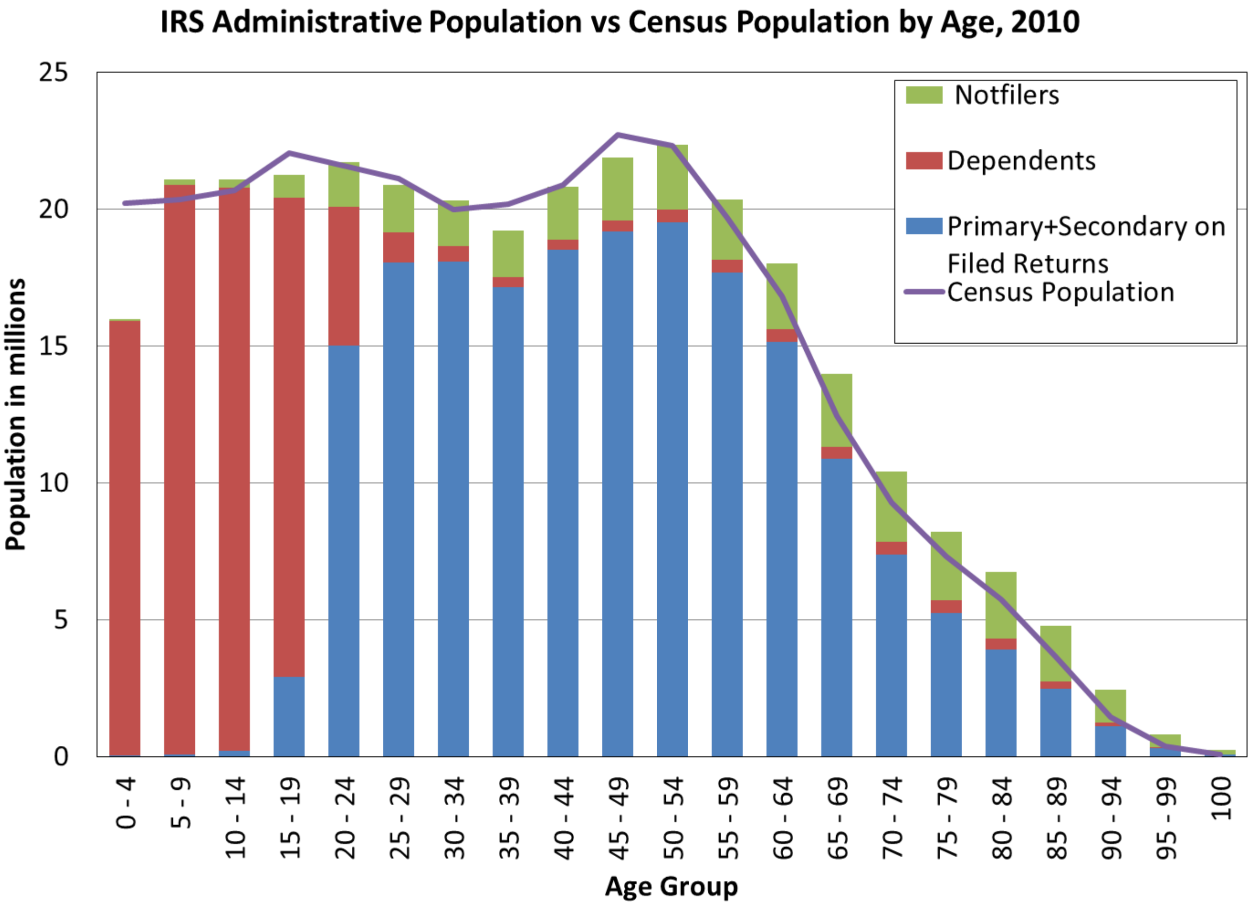
# Efforts to Correct CPS-Based Underestimates of Required Population

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

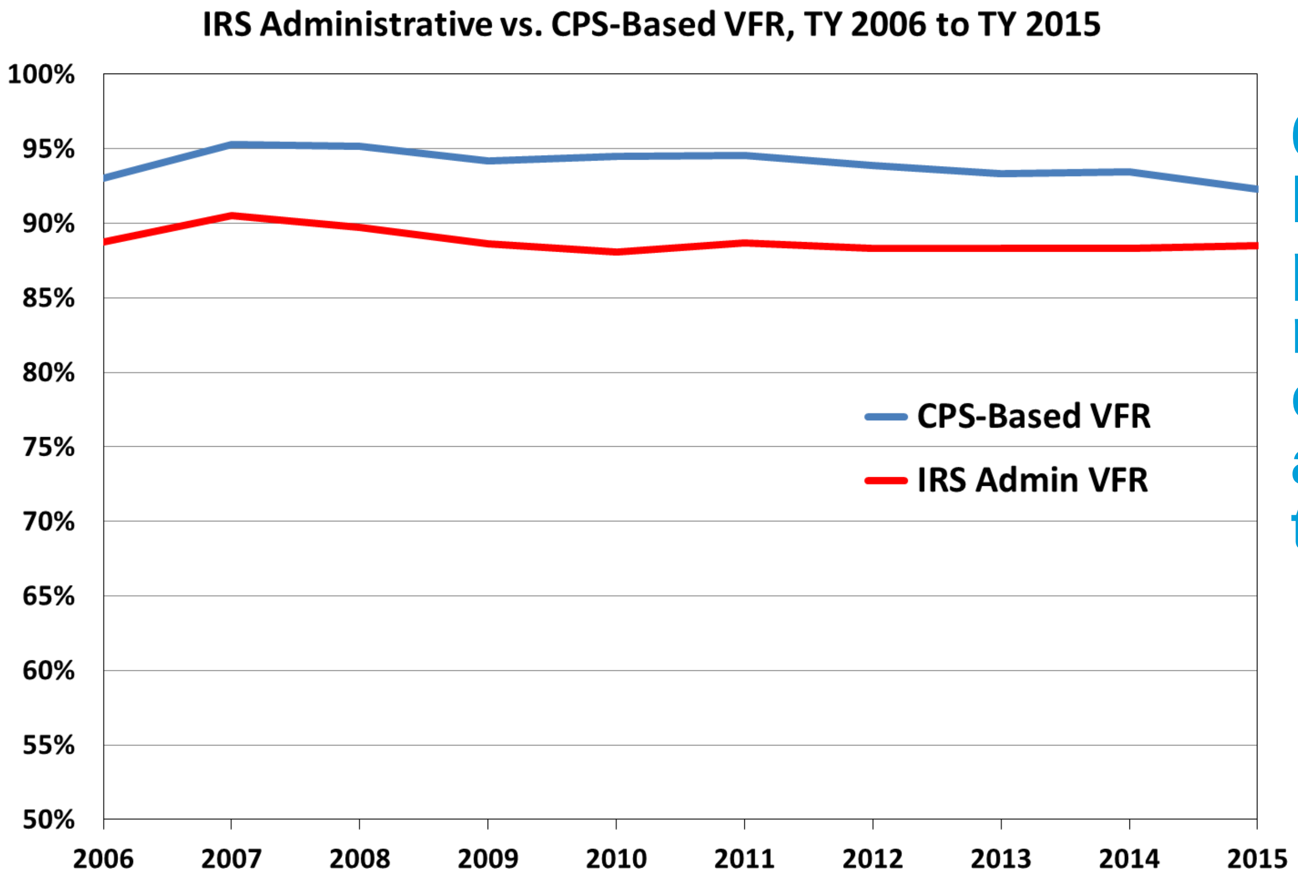
Result not satisfactory. Significantly lower VFR estimates for Tax Year 2007 than subsequent years. This contradicts expectations and evidence from IRS administrative data that because of stimulus credits the VFR should be higher in this year.

# 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.

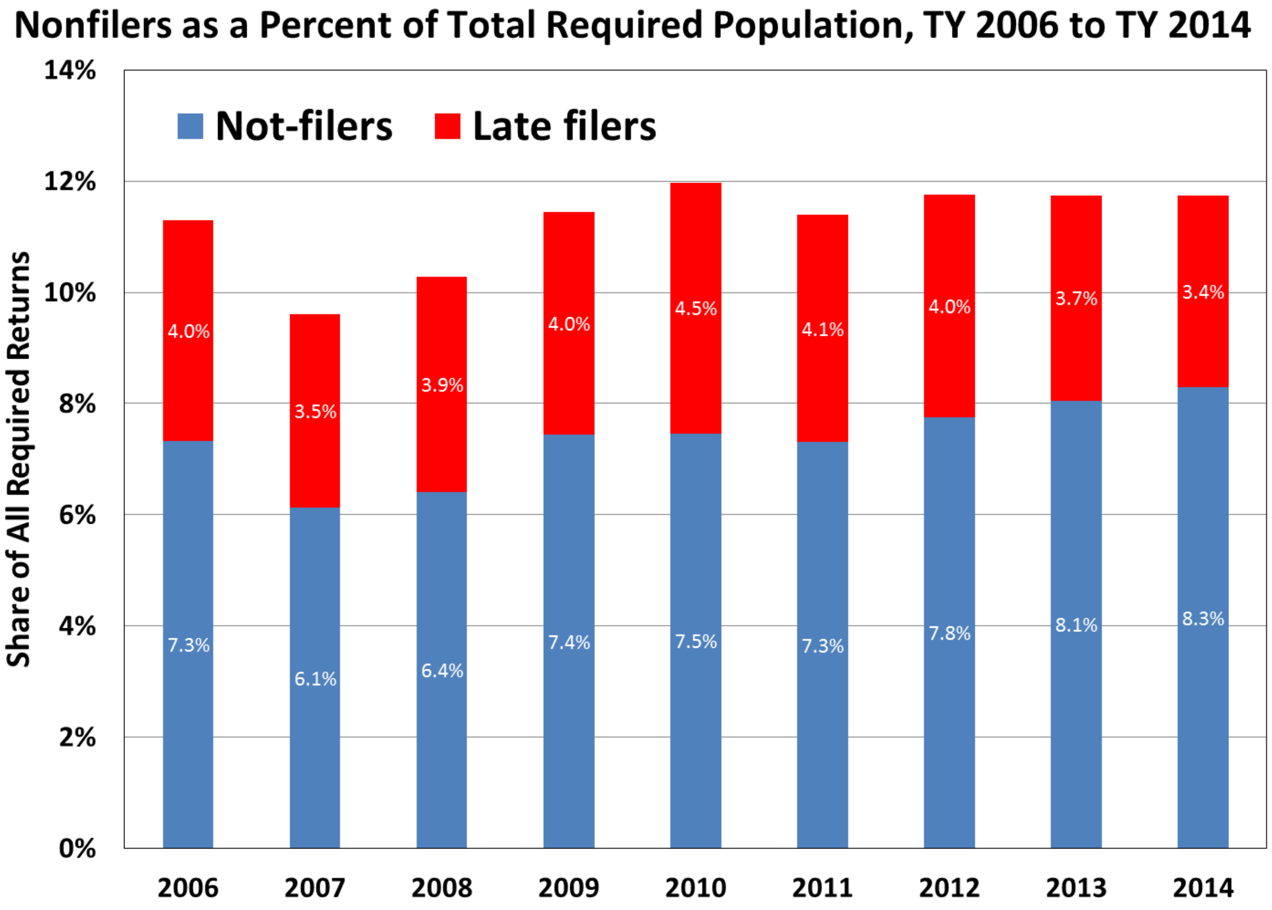



# IRS population is fairly close to US Census population estimates

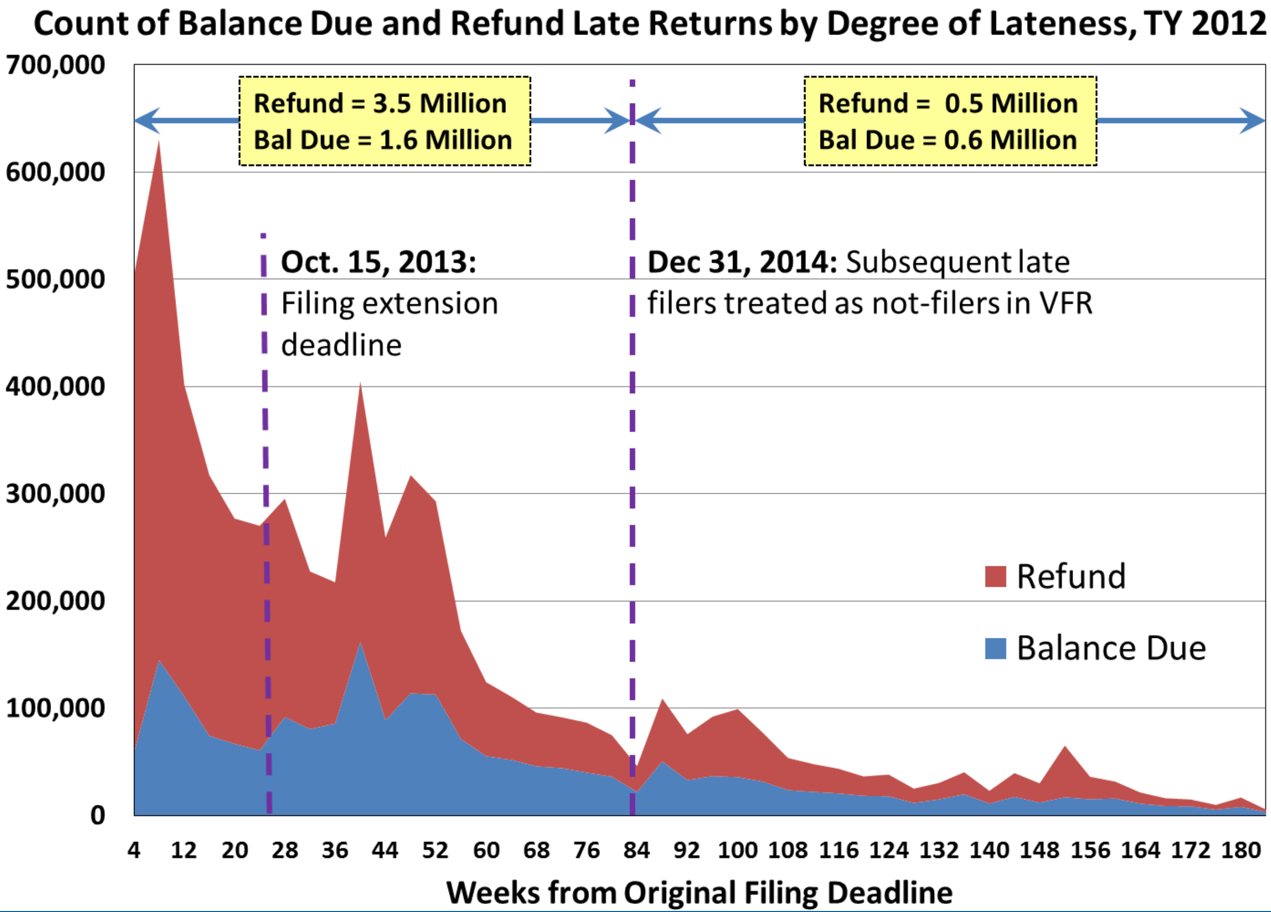



Note: The 2015 IRS Administrative Data-based VFR is provisional.

**6.5% (~8 million) larger required population, results in VFR estimate that is about 5% lower than CPS method**

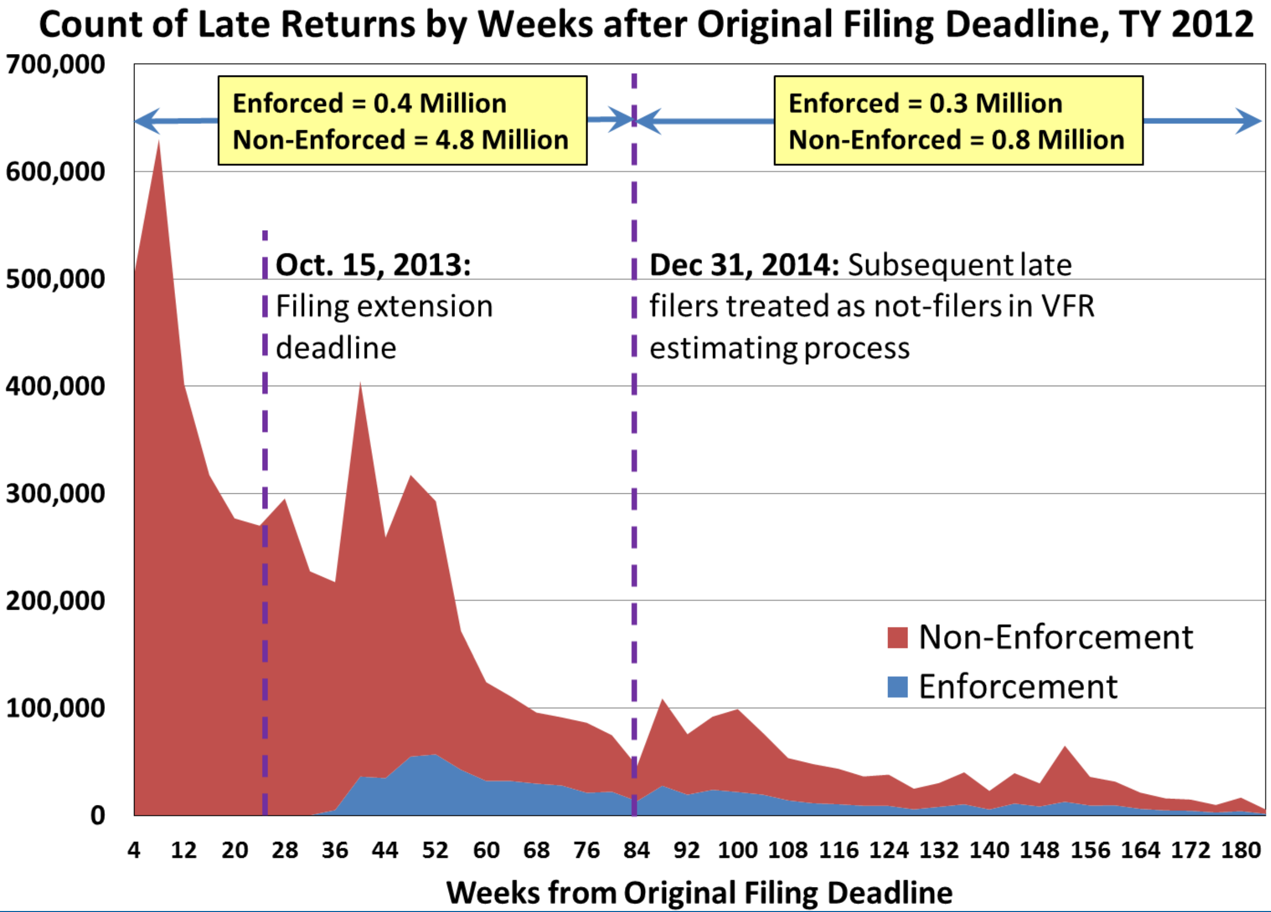



## The late-filer portion of nonfilers has declined in last few years, presumably due in part due to reduced nonfiler enforcement




## Returns with refunds make up large share of returns filed in the first months after deadline but smaller share later

## Count of Late Returns by Weeks after Original Filing Deadline, TY 2012

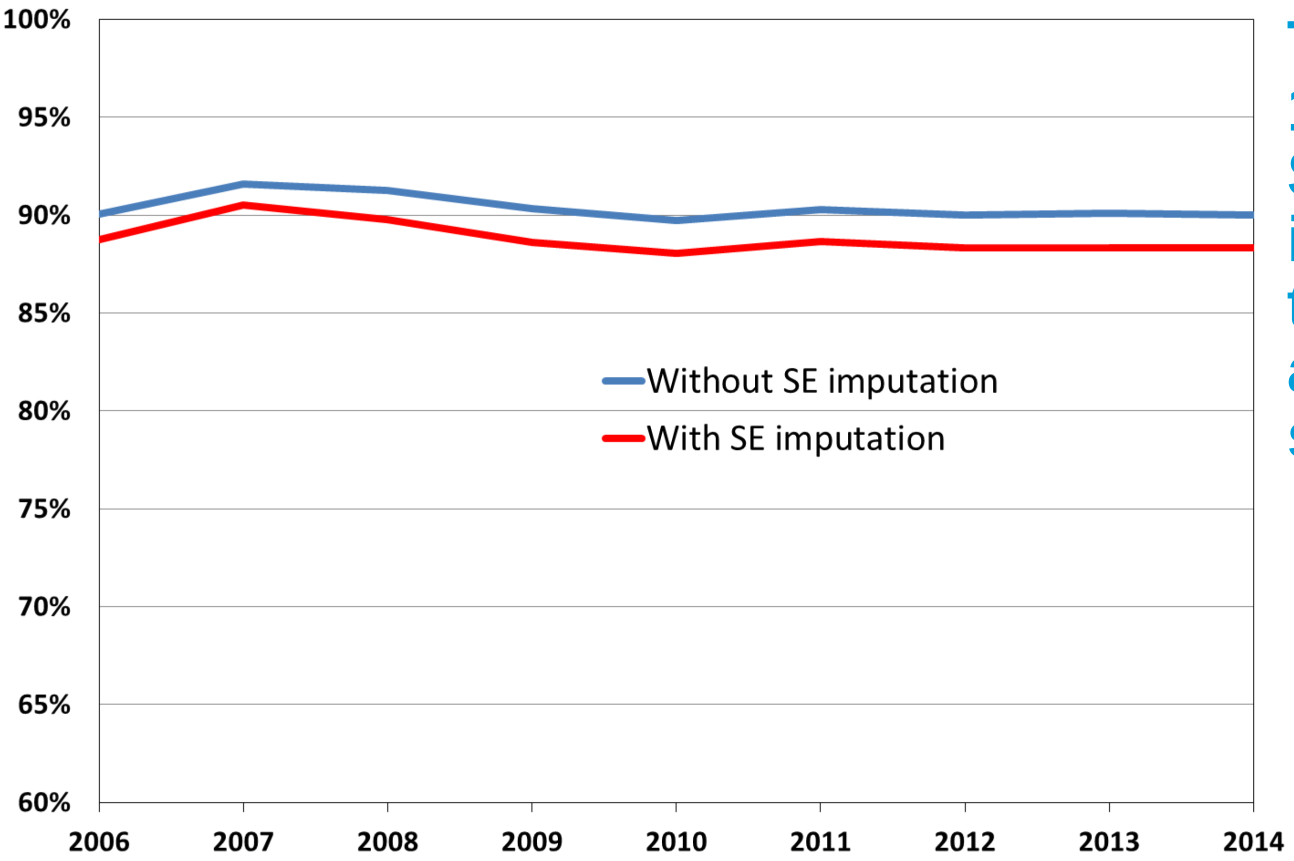



- Most non-enforced late returns are filed within two years.
- Returns secured through enforcement peak about one year after the filing deadline
- Not a large number of returns in third and fourth years after end of tax year so no significant loss in accuracy

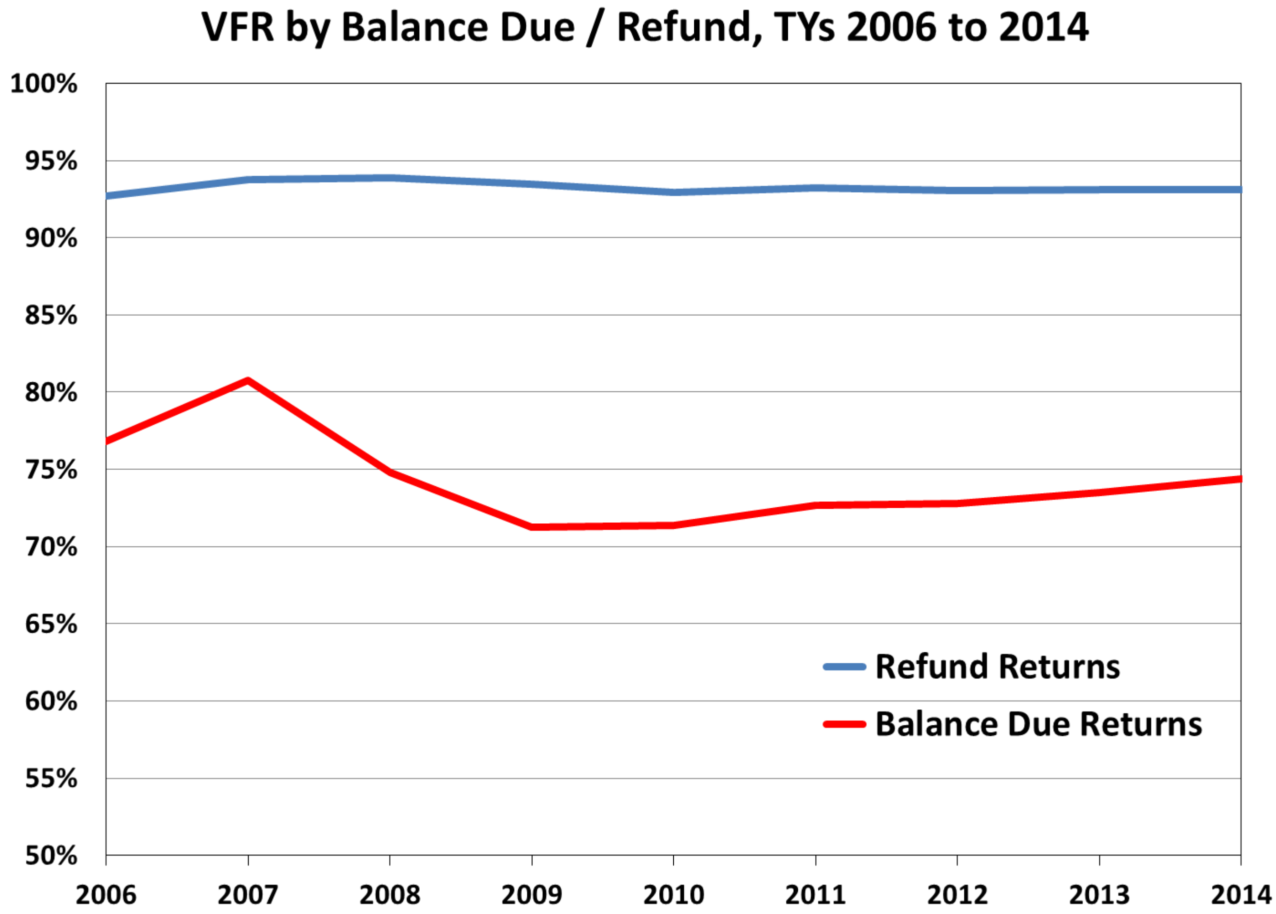
# Characteristics of Nonfilers and Drivers of Nonfiling

- 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

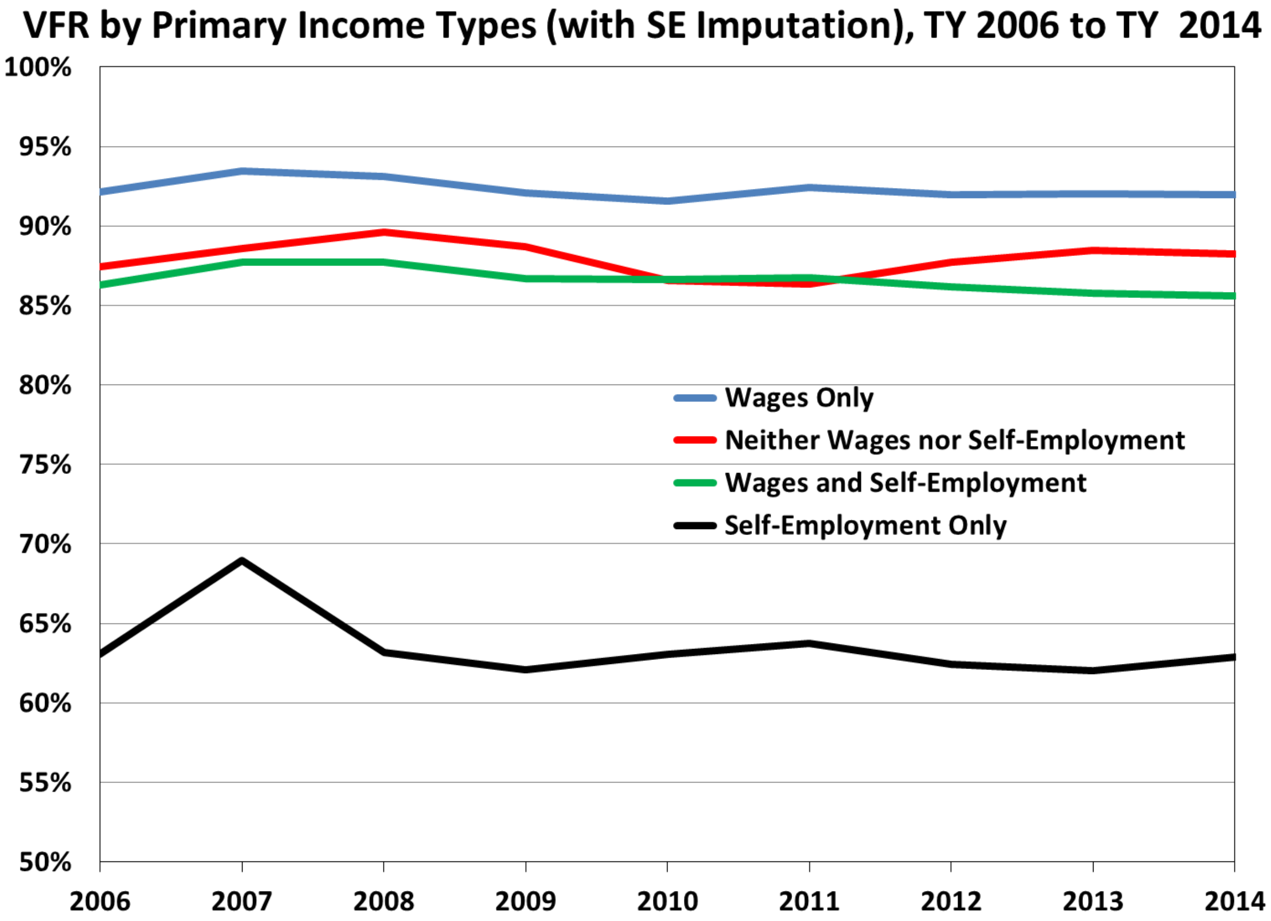
## VFR with and without Imputation of Self Employment Income, TY 2006 to TY 2014



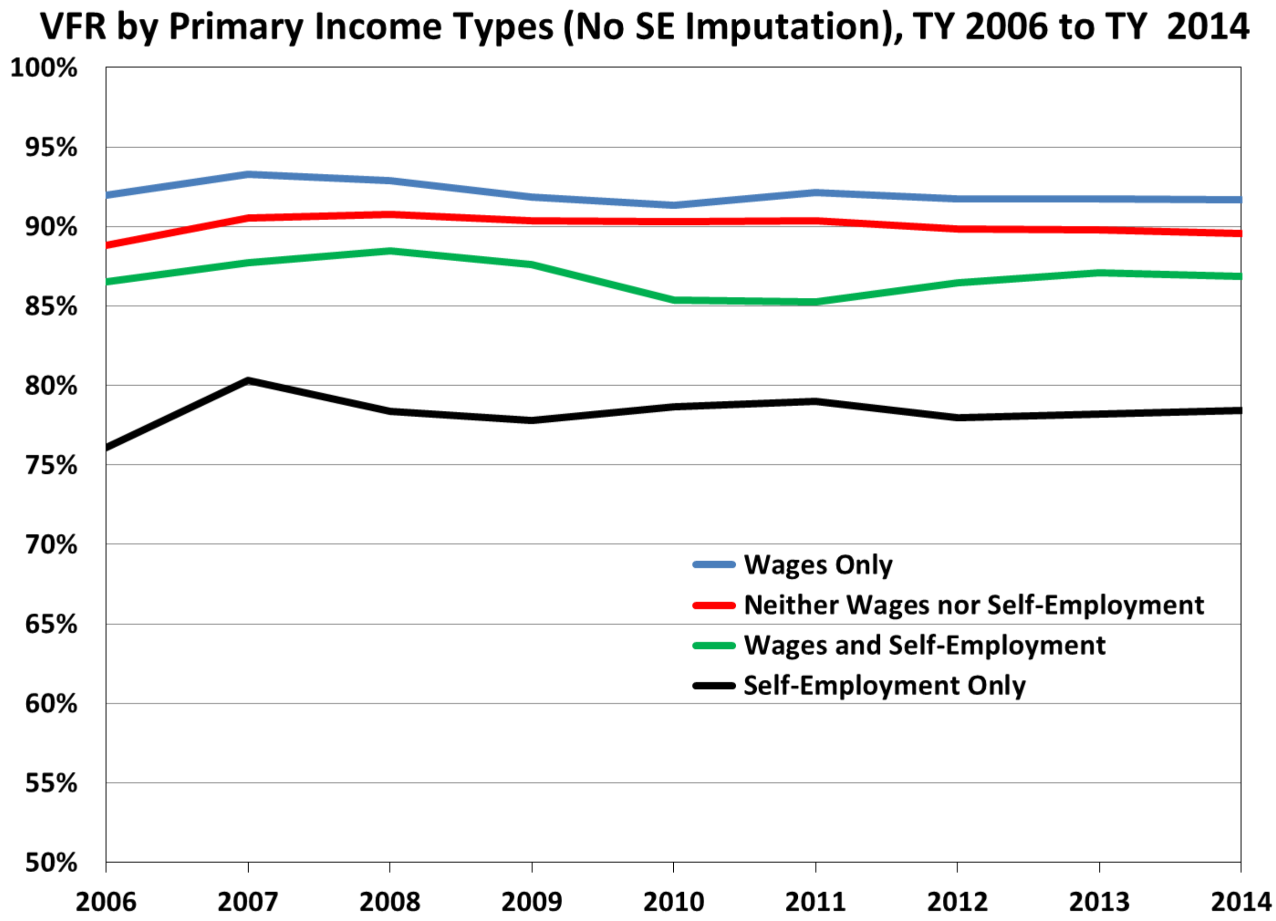

**The VFR is about 1.6% lower with SE income imputation, but the trend with and without is similar**




**The VFR is stable and high for those owed a refund; much lower and less stable for those with a balance due**

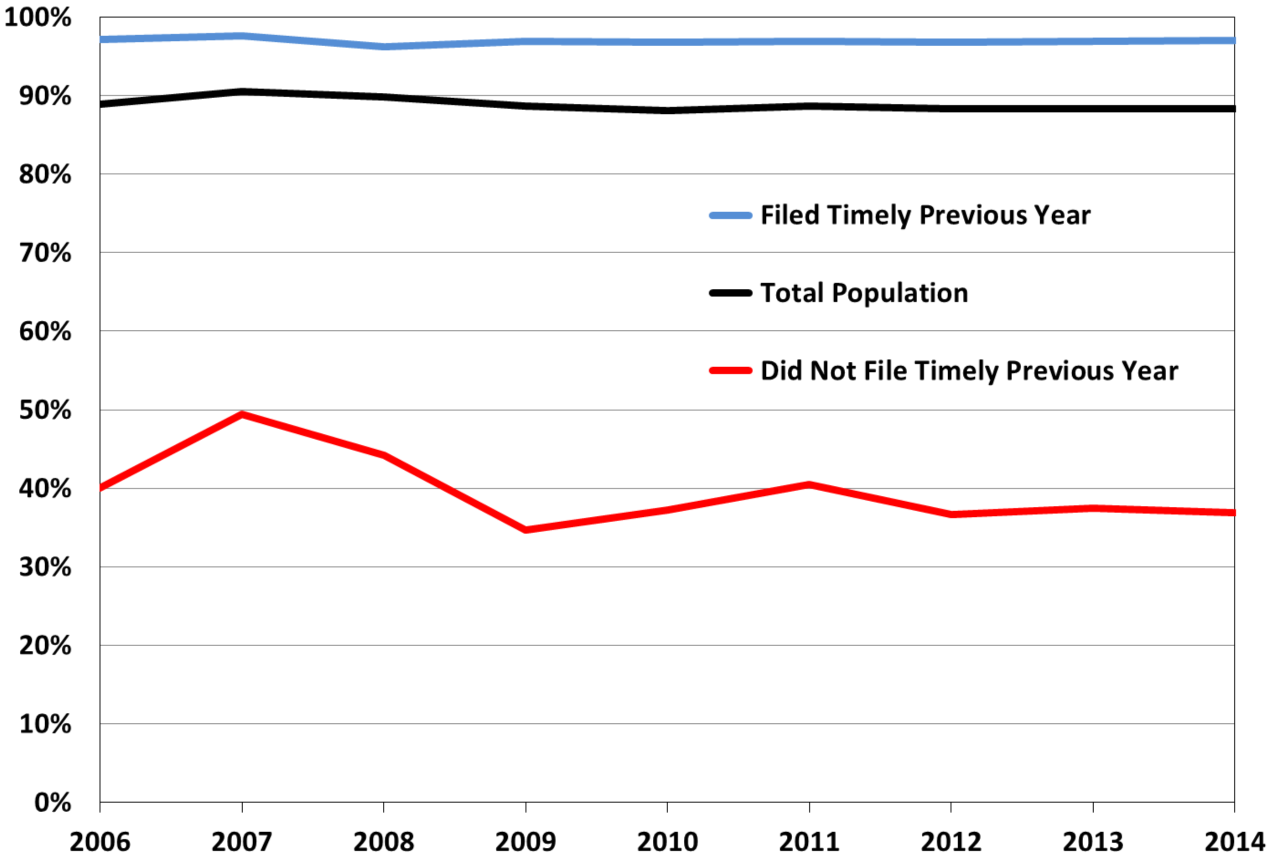



## The VFR is much higher for those whose earned income is limited to wages and much lower for those with only SE income

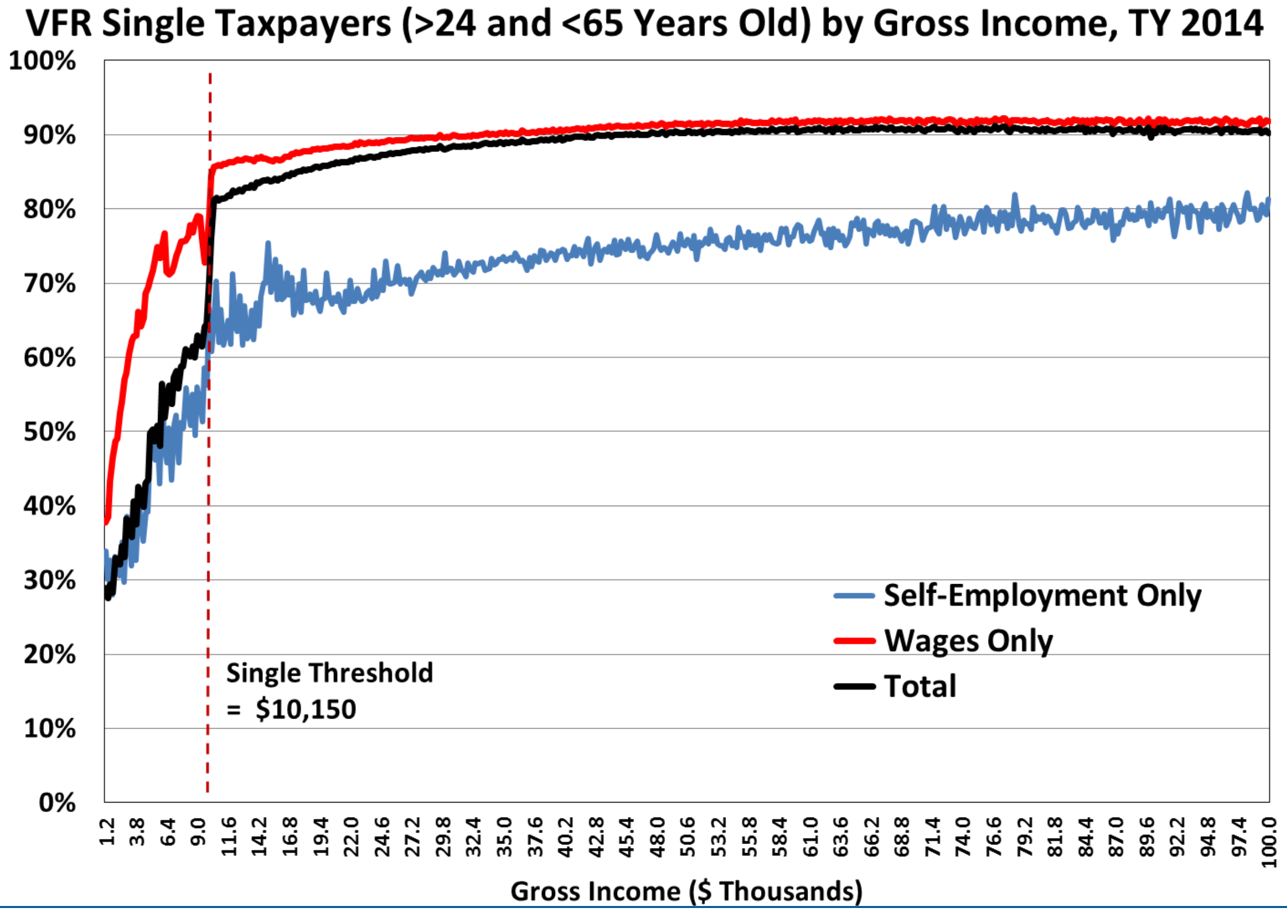



## This is true even when SE imputation is removed, though difference in VFR is less

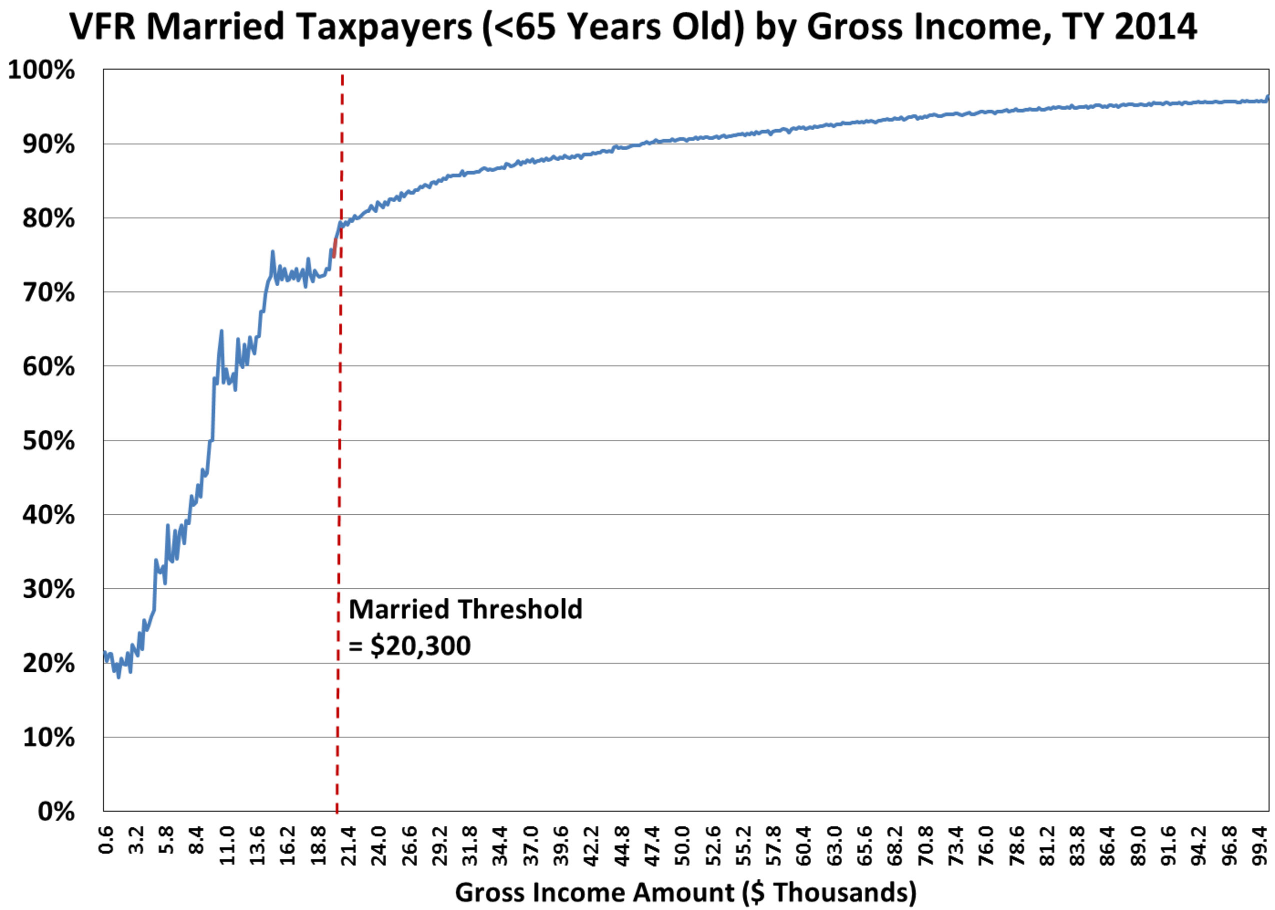
## VFR for Taxpayers Who Filed Timely in the Previous Year vs. Those Who Did Not



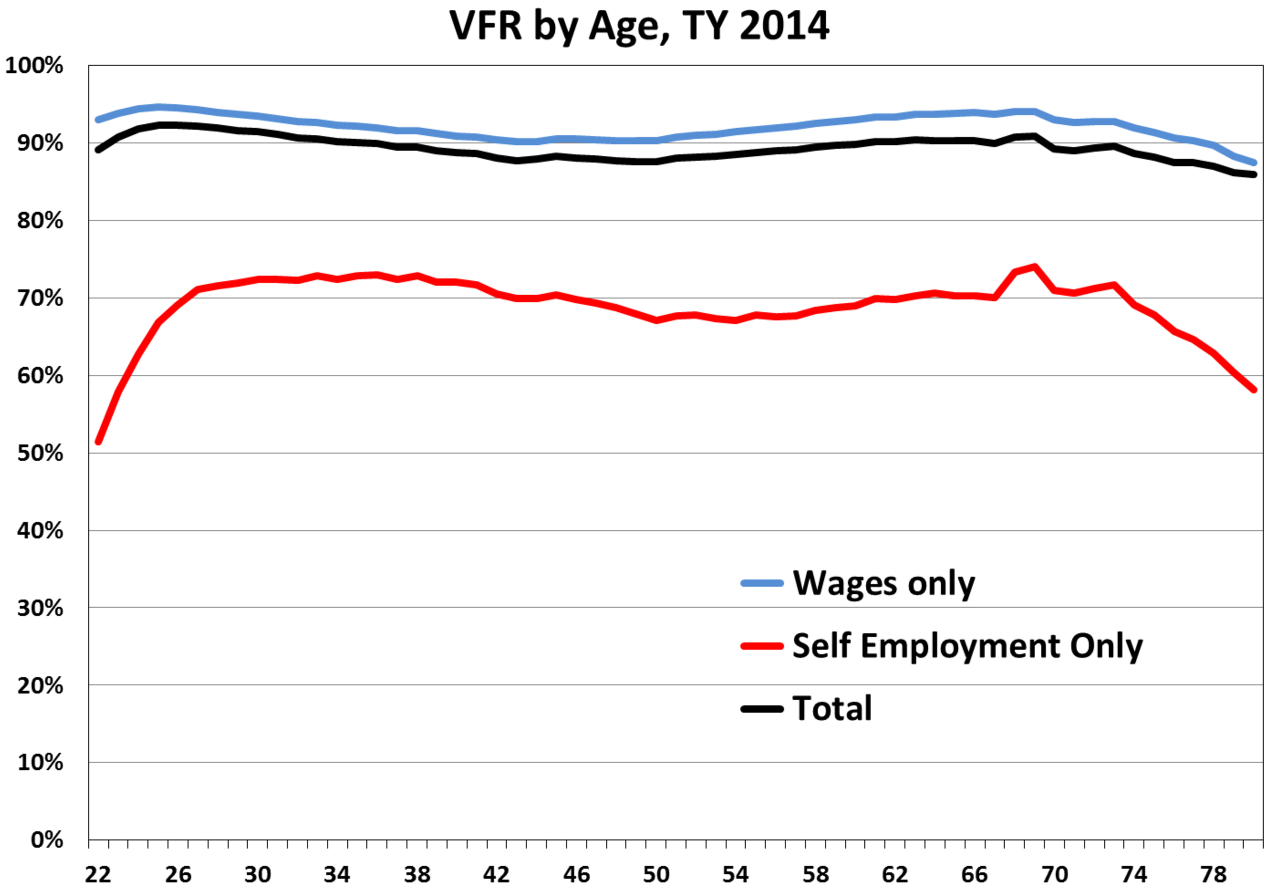

# VFR is much higher for those who filed timely in the previous year



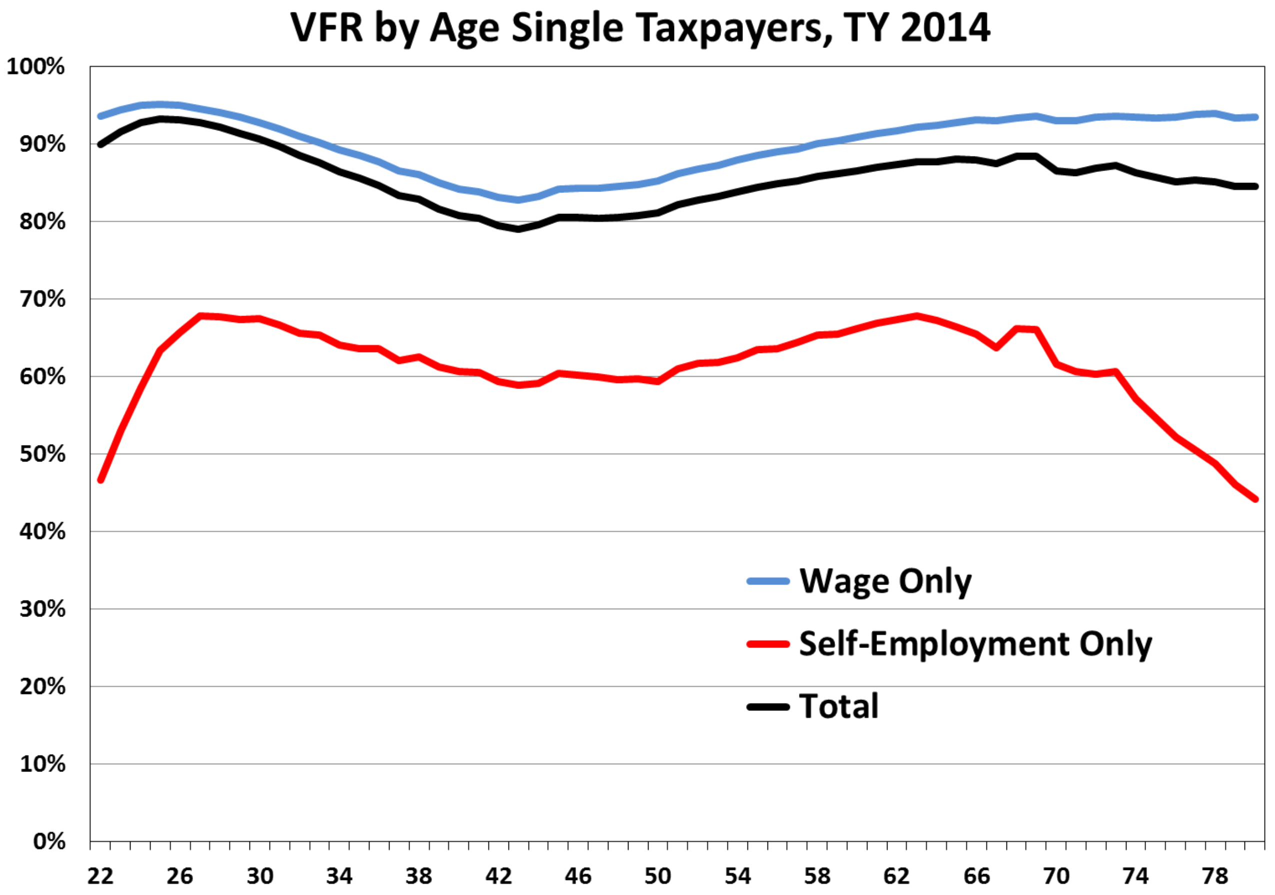

# VFR (for given gross income bin) increases as gross income increases relative to the filing threshold



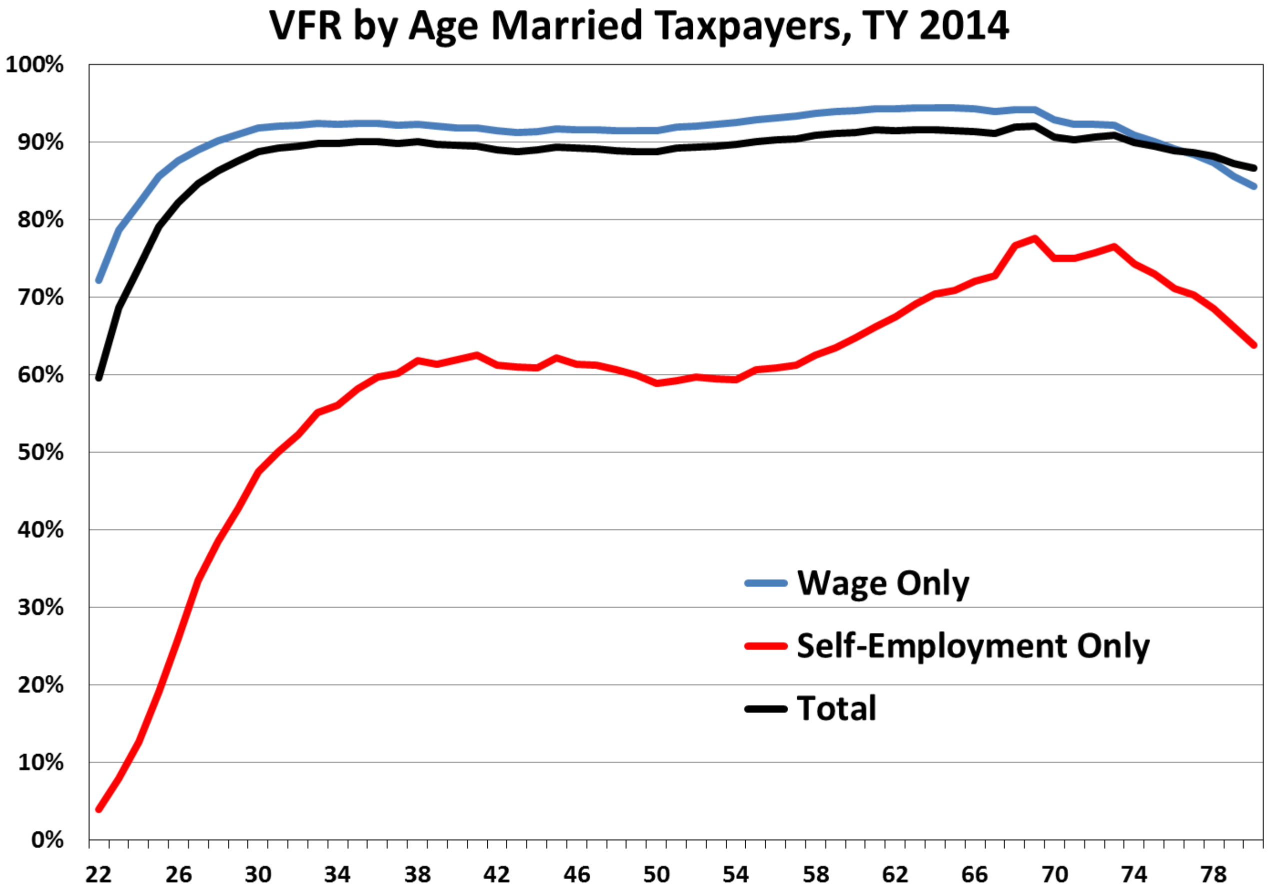

## Similar pattern for married taxpayers



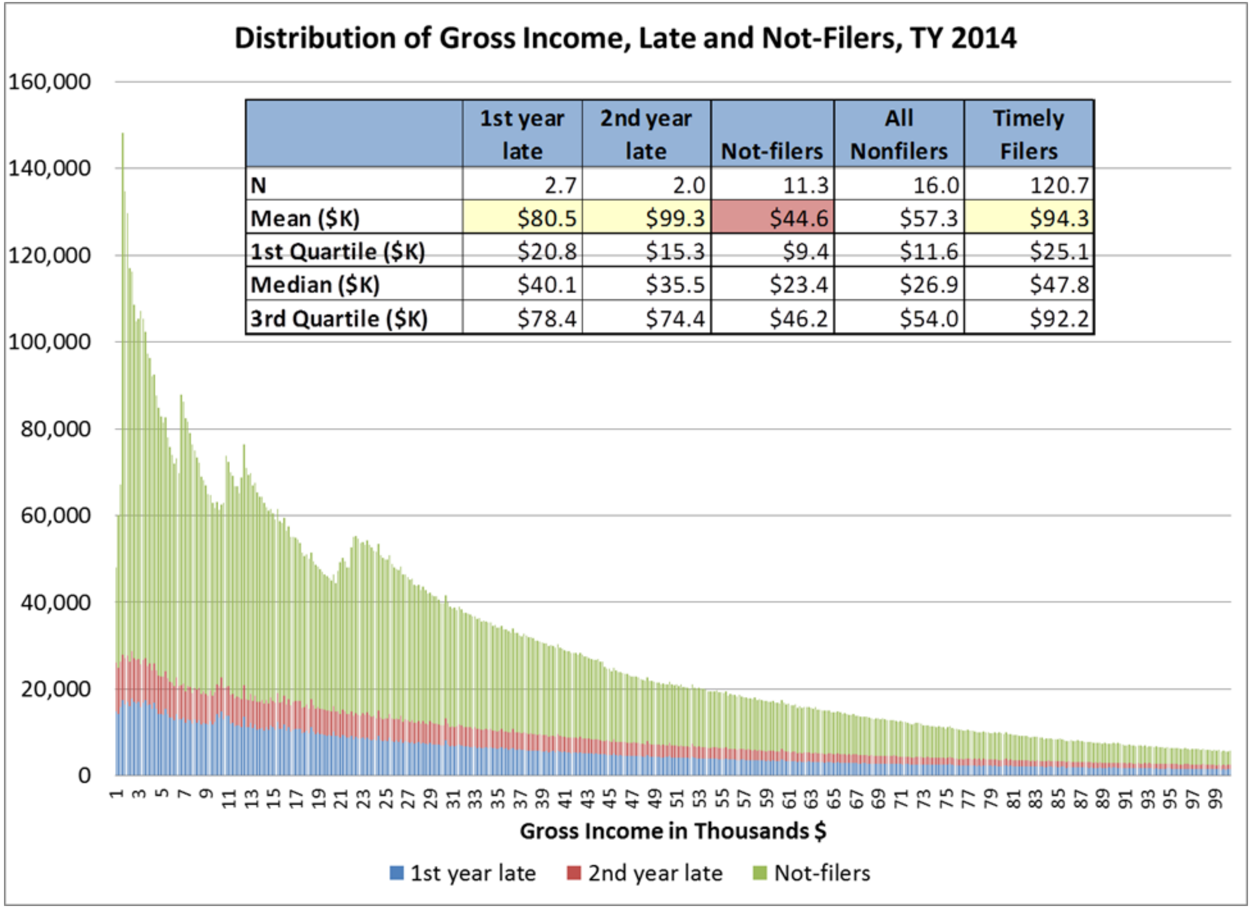

## Lower VFR for middle age taxpayers and later ages; unclear which underlying variables lead to dip in filing




# Pattern more pronounced for single taxpayers

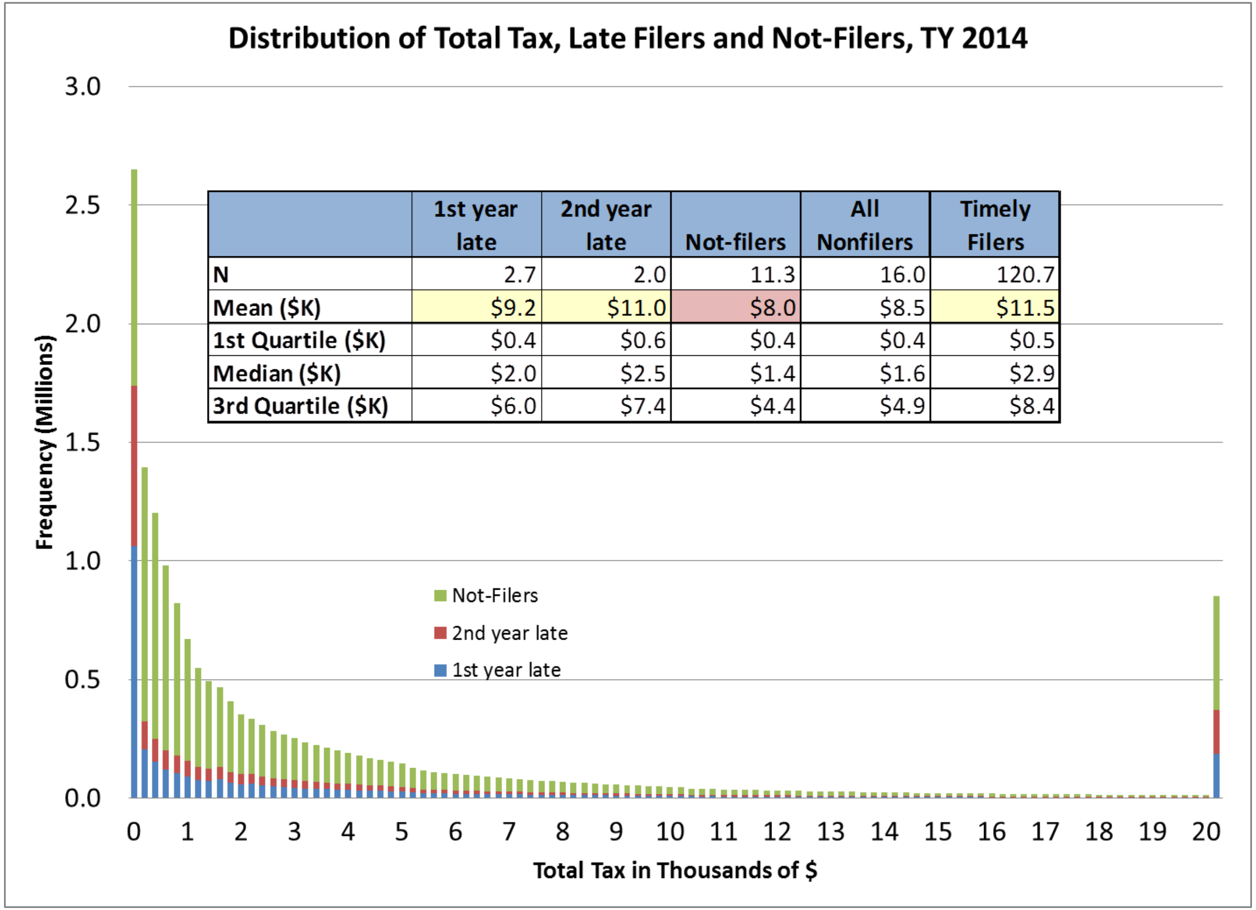



## But, less pronounced for married taxpayers



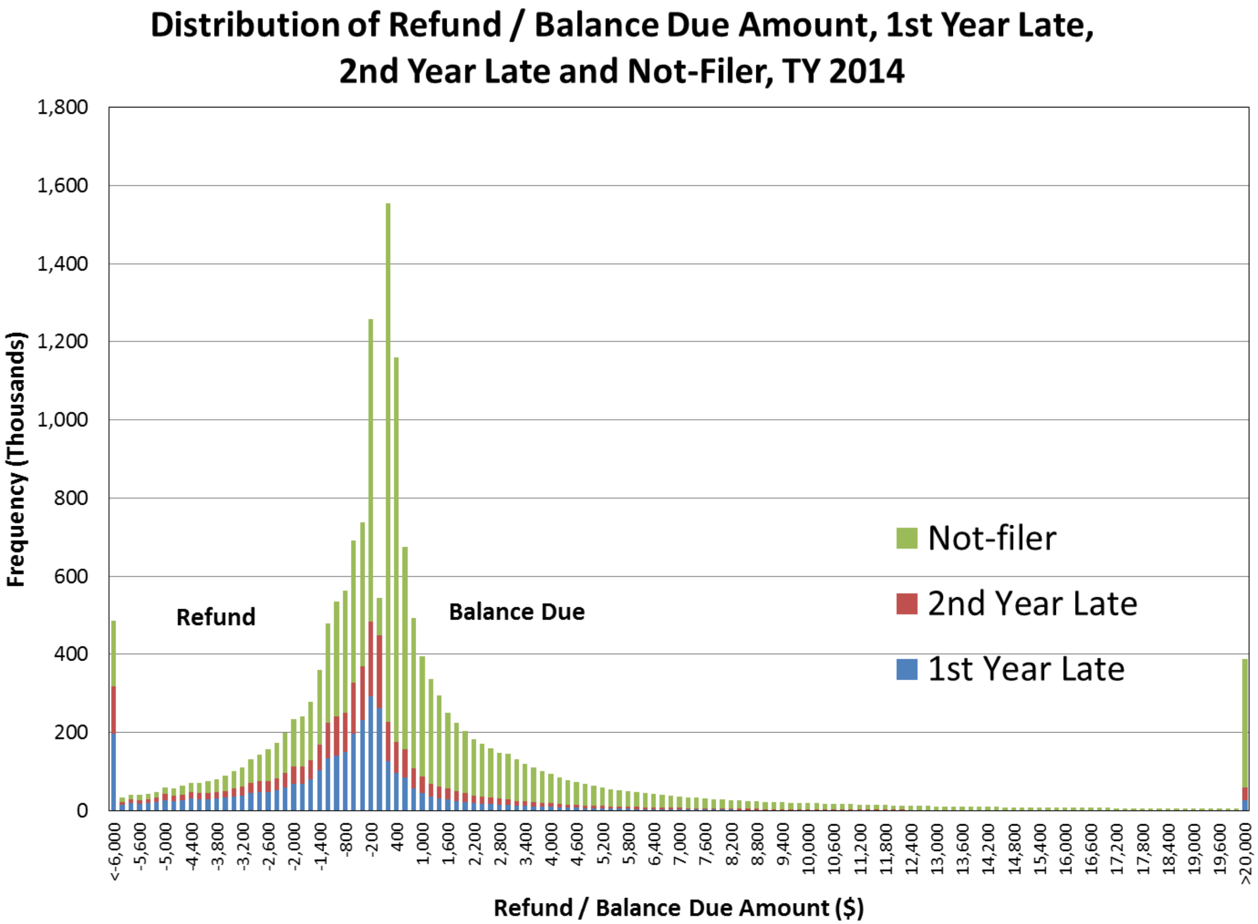

| | 1st year late | 2nd year late | Not-filers | All Nonfilers | Timely Filers |
|---|---|---|---|---|---|
| N | 2.7 | 2.0 | 11.3 | 16.0 | 120.7 |
| Mean ($K) | $80.5 | $99.3 | $44.6 | $57.3 | $94.3 |
| 1st Quartile ($K) | $20.8 | $15.3 | $9.4 | $11.6 | $25.1 |
| Median ($K) | $40.1 | $35.5 | $23.4 | $26.9 | $47.8 |
| 3rd Quartile ($K) | $78.4 | $74.4 | $46.2 | $54.0 | $92.2 |

- **Distribution of gross income among nonfilers has a long tail**
- **Late filer and timely filer average gross income higher than for not-filers**




| | 1st year late | 2nd year late | Not-filers | All Nonfilers | Timely Filers |
|---|---|---|---|---|---|
| N | 2.7 | 2.0 | 11.3 | 16.0 | 120.7 |
| Mean ($K) | $9.2 | $11.0 | $8.0 | $8.5 | $11.5 |
| 1st Quartile ($K) | $0.4 | $0.6 | $0.4 | $0.4 | $0.5 |
| Median ($K) | $2.0 | $2.5 | $1.4 | $1.6 | $2.9 |
| 3rd Quartile ($K) | $6.0 | $7.4 | $4.4 | $4.9 | $8.4 |

## 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