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More Than Meets the Eye: The Comprehensive General Indirect Effect of Auditing Individual Income Tax Returns*

Alan Plumley and Daniel Rodriguez
IRS Research, Applied Analytics, and Statistics

Jess Grana and Miguel Sarzosa
MITRE

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Abstract

IRS audit rates have generally fallen for over a decade due to declining resources. In addition to loss of direct revenue, decreased enforcement likely results in increased noncompliance, as well. We contribute to a small literature on the "comprehensive" indirect effects of IRS enforcement on voluntary compliance across the general taxpayer population—mostly those who were not directly subject to the enforcement. Using microdata from random audits conducted for research purposes, we find that misreporting increases on certain tax return line items as overall audit rates decline. As we might expect, these effects are more pronounced for line items that are the typical target of audits rather than line items addressed through the automated matching program. We translate effects on misreporting into effects on tax revenues and compare revenues against enforcement costs. We find that over the Tax Year 2006-2014 period, the overall average marginal return on investment (ROI) of IRS individual tax enforcement was between 13:1 and 16:1, including a direct average ROI of 3:1 and an indirect average marginal ROI between 10:1 and 13:1. In other words, for this time period, the general indirect effect was 3 to 4 times the direct revenue effect. These ROI estimates advance current understanding of the IRS's overall impact and can inform budgetary discussions.

Keywords: Tax audits, Spillovers, General Indirect Effect, ROI of audits

JEL Codes: H23, H26

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1 Introduction

How much additional revenue could be generated if the enforcement budget for the Internal Revenue Service (IRS) were increased by $X per year? The answer to that question is far from simple; it depends on the size of the current budget and how it is allocated to enforcement, services, IT investments, and other activities. It also depends on how the enforcement budget is allocated to the various enforcement programs. One impact on overall revenue would come in the form of increased *direct* enforcement revenue – additional tax collections resulting from the enforcement action for the tax year being enforced. Moreover, it is likely that the direct effect would be accompanied by some *indirect* revenue effects—whether due to a subsequent change in compliance behavior among the specific taxpayers who were the subjects of the enforcement (known as the "specific indirect effect"), and/or a spillover due to a change in compliance behavior among taxpayers in the general population who were *not* the subjects of the enforcement (known as the "general indirect effect"). Estimating the spillovers of enforcement, and thus the full extent of the return to investing in tax enforcement, is not straightforward, but it is extremely important. The IRS 2024 budget request to Congress is a testament to this. It cites a return on investment (ROI) in terms of direct revenue but "does not include the indirect effects of IRS enforcement activities on voluntary compliance" (IRS, 2024). This paper intends to fill this gap.

There have been numerous attempts over the last 40 years to estimate the general indirect effect of changes in IRS enforcement—particularly changes in audit coverage rates. These efforts fall within two approaches: (1) "local network" models; and (2) "comprehensive" models. Local network models attempt to demonstrate that a general indirect effect exists in a particular context. For example, they estimate the general indirect effect within a given segment of the population (e.g., sole proprietors) through a specific type of network (such as the network of taxpayers who are clients of the same tax preparer) and according to a particular behavioral mechanism (e.g., deterrence). Using well-defined networks supports strong identification strategies whereby a treatment group (i.e., a network that had an audited member) is compared against a similar but untreated group. A drawback of local network models is that they are context-specific.[1] Their findings may not be generalizable outside of the specific context or behavioral mechanism studied. Taxpayers presumably participate in multiple networks simultaneously (e.g., employer networks, professional networks, community networks, etc.), and it is unclear whether the separate impact of these networks are additive. Taxpayers undoubtedly form their perceptions in a more subtle way based on all the factors in their environment.

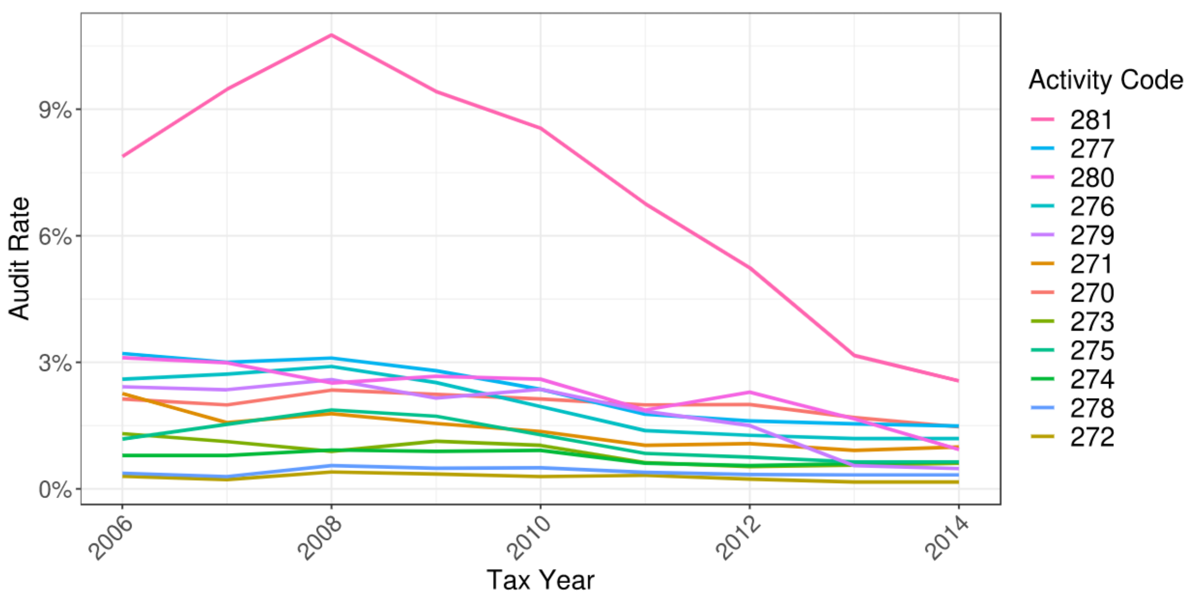
Although local network models lend themselves to theoretical premises and practical experimentation, such narrowly defined analyses do not directly translate into operational applications such as budget justification. To achieve that, the estimated indirect effects should in theory include effects arising: 1) from all IRS enforcement activities; 2) across the general taxpayer population; and 3) across all possible (or as many as possible) networks of propagation. Comprehensive models are better suited for these purposes as they are agnostic about the

[1] For instance, studies like Boning *et al.* (2020), Badgley *et al.* (2021), and Chetty (2013) show large spillovers of audits that spread through networks of different kinds. Others that explore more light-touch interventions like mailing letters shaming delinquent tax filers find mixed or no evidence of an indirect effect (Meiselman (2018); Perez-Truglia and Troiano (2018); Grana *et al.* (2022)). These mixed results indicate that context matters: the existence and size of an indirect effect depend on the specific network or community studied or even on research design choices.

mechanism(s) affecting taxpayer behavior and are generally not restricted to a narrow subset of the population. However, their identification is less straightforward. They depend heavily on being able to control for all the main drivers of behavior in addition to the enforcement activity in question.

This paper estimates a comprehensive model of the impact of individual income tax audits on the general population. It is motivated by the observation that, due to a steady decline in IRS budgets over the last 12 or so years, overall individual income tax audit coverage rates (the percentages of any given subpopulations that are audited) have declined substantially, going from 1% in 2008 to less than 0.6% in 2014 (see Figure 3 in the Appendix). Despite the overall decline, audit rates did not fall uniformly across Examination Activity Codes—IRS' groupings of taxpayers based on Total Positive Income[2] (TPI) level, the filing of certain schedules, and the claiming of the Earned Income Tax Credit (EITC).[3] For instance, while audit rates fell from 10.8% in 2008 to 2.6% in 2014 for those earning \$1,000,000 or more (Activity Code 281), Figure 1 shows that audit rates in other Activity Codes remained somewhat stable and, in some instances, they even increased at various points in time.

Figure 1. Audit Rates by Activity Code

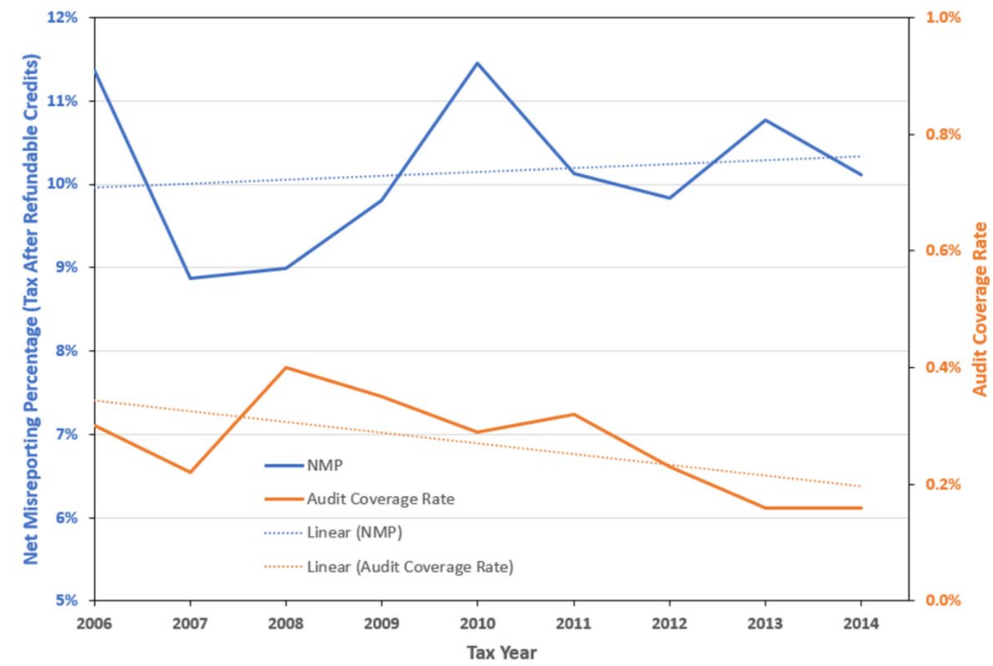


Descriptive evidence suggests the existence of co-movement between audit rates and noncompliance—measured by the Net Misreporting Percentage (NMP) on tax after refundable credits (TARC).[4] As an example, Figure 2 illustrates the audit coverage and misreporting rates

[2] TPI is the sum of all positive amounts of income and excludes income losses, such as from investments.
[3] See the lists of Activity Codes, their definitions, and their relative importance as percentage of the taxpayer population in Table 7 of the Appendix.
[4] The NMP is defined as the aggregate net amount misreported on a given line item across a group of returns divided by the sum of the absolute values of the corresponding amounts that should have been reported. The absolute values are used in the denominator to ensure that negative amounts do not distort the aggregates. These misreporting statistics were compiled from data generated by audits of a stratified random sample of tax returns each year under the IRS National Research Program (NRP).

for individuals in Activity Code 272 (i.e., those whose returns fall below $200,000 in TPI and which are not accompanied by supplemental forms like Schedule C, E, F or Form 2106[5] and do not claim the EITC). This group comprises over half of all individual tax returns. Figure 2 shows an overall upward trend in noncompliance contemporaneous with a declining trend in the audit coverage rates over these years, suggesting the presence of a general indirect effect among this large group of taxpayers.

Figure 2. Audit Coverage and NMP Trends, TYs 2006-2014 for Taxpayers with TPI <$200k and no EITC, Schedule C, E, F or Form 2106 (55.3% of the Population)



In addition to an overall compliance response to changes in audit coverage, we further hypothesize that this effect varies by the *visibility* of income and other tax return line items. Compliance is more likely to be affected on line items that are often targets of audits. Line items subject to automated matching programs (which are not audits) may be less affected by changing audit rates.

This paper adds to the literature on the indirect effect of audits by using alternative model specifications and exploiting new individual microdata to capture noncompliance. We differ from prior research in our econometric specification: instead of the contemporaneous audit rate, we evaluate the effect of a lagged audit rate on compliance. Taxpayers do not have contemporaneous knowledge of the audit rate since information disseminates with a lag. Moreover, the IRS's estimate of the risk that a given return is noncompliant is also not contemporaneous; it is based on audit results of similar returns from prior years. The significance of these lags is that they reduce endogeneity concerns arising from reverse causality. We also differ from prior work by

[5] Schedules C and F are used to report nonfarm and farm sole proprietor income and expenses, respectively; Schedule E is used to report income from rental real estate, royalties, partnerships, S corporations, estates, trusts, or residual interests in real estate mortgage investment conduits; and Form 2106 is used to report employee business expenses.

exploring how the compliance response differs across groups of line items based on how visible the line item is to the IRS through third-party reporting.

Our findings largely confirm the hypothesis that individual misreporting responds to audit rate changes differently across visibility groups of line items in ways consistent with the extent of the visibility. We translate the impact of audit rates on the *misreporting* of income or offset amounts to the impact on *tax revenues*. Then, comparing revenues against enforcement costs, we calculate the overall return on investment (ROI) of audits of individual income tax returns. We find that, on average, \$1 spent on individual income tax audits generates about \$3 of direct revenue and an additional \$10 to \$13 of indirect revenue (roughly 3 to 4 times the direct revenue). Our findings are within the range of magnitude estimated by a handful of prior studies and close to the estimate put forward by the U.S. Treasury indicating that the indirect effect is three times the direct effect (Department of the Treasury, 2019).

The paper is organized as follows: Section 2 reviews the relevant empirical literature and provides theoretical motivation for this research; Section 3 describes our data; Section 4 summarizes our estimation methods; Section 5 presents our empirical results; and Section 6 concludes.

2 Background and Theoretical Motivation

The decision to declare taxes is made under uncertainty. That is because a taxpayer's failure to fully report their income does not automatically trigger punishment from tax authorities. If a taxpayer underreports income, the reward of doing so will depend on whether or not they are investigated by the authorities. If they are not investigated, they are better off underreporting than declaring their full income. However, if they are investigated and the penalty for underreporting is greater than its benefits, they are worse off. That is why in the classical economic theory of tax compliance, rational (risk-averse) individuals maximize the expected utility of the tax evasion gamble, purposefully comparing the expected monetary benefits of gaming the tax system against the risky prospect of detection and punishment (Allingham and Sandmo, 1972). A key parameter in this context is, of course, the probability of detection. A well-established result in the classical economic theory of tax compliance is that an increase in the probability of detection will always lead to more income being declared (Lopez-Luzuriaga and Scartascini, 2019). That is because a higher probability of detection reduces the expected payoff of underreporting.

Incidentally, this is the theoretical foundation for the existence of the general indirect effect of audits that we explore in this paper—the effect of IRS contacts (such as audits) on those who are mostly not contacted themselves. It is not the fact that the person is audited, but the chances of someone getting audited that drive the change in tax reporting. Early empirical evidence supports this result. Studies like Dubin and Wilde (1988), Dubin, Graetz and Wilde (1990), Tauchen, Witte and Beron (1993), and Plumley (1996), which we refer to as measuring the "comprehensive indirect effect", find that higher aggregate (e.g., state or ZIP code level) contemporaneous audit *rates* on the general population (as a proxy for audit probability) are associated with greater tax compliance. For example, using state-level panel data, Dubin, Graetz and Wilde (1990), Plumley (1996), and Dubin (2007) find that the comprehensive indirect effect of audits is six, eleven, and nine times that of the direct effect, respectively. Dubin and Wilde

(1988) and Grana *et al.* (2022) use zip-code level panel data and find mixed evidence of an indirect effect, varying across taxpayer subpopulations and audit categories (see Table 1).

Table 1: Findings from Prior Studies on the Comprehensive General Indirect Effect

Ratio of Indirect to Direct Revenue (not ROI)	
2:1 (high-income taxpayers only)	Tauchen, Witte, and Beron (1993)
6:1	Dubin, Graetz and Wilde (1990)
9:1	Dubin (2007)
11:1	Plumley (1996)
Mixed evidence	Dubin and Wilde (1988) and Grana *et al.* (2022)

However, contemporaneous audit rates are not public knowledge. So, if national audit rates are abstract or distant from the day-to-day concerns of individual taxpayers, how can they have a significant impact on tax reporting behavior? Taxpayers must build perceptions about them from partial information gathered through various channels. The analyses of some of those channels build a complementary and larger body of knowledge within the general indirect effects literature. This sub-strain of the literature incorporates "local network" models that focus on a single context and channel of information transmission.

One of those channels is tax preparers. Professional tax preparers closely monitor national audit rates to better advise their clients. If audit rates are high, tax preparers may be more diligent in ensuring compliance and advising clients to avoid aggressive tax positions. This professional guidance influences taxpayers' behavior, even if they are not directly aware of the audit statistics (Keppler, Mazur and Nagin, 1991). Boning *et al.* (2020) and Badgley *et al.* (2021) show that professional tax preparers also catalyze a network effect on tax reporting. They find that taxpayers who share tax preparers with IRS-visited/audited taxpayers tend to report more income to the tax authorities.[6] That may be because the tax preparer becomes aware firsthand of the possibility of misreporting detection and transfers that information to their other clients who update their perceptions about the detection probability they face.

A similar channel through which aggregate audit rates can inform individual's perceptions on their chances of detection, akin to that of tax preparers, comprises taxpayers' social networks. As with tax preparers, this channel relies on making the taxpayer aware that she could have been audited (or not) as their peers, family members, or colleagues have (or have not) been. This channel's effects capture responses driven by information about enforcement spread through the network by word of mouth. As shown by Chetty *et al.* (2013) when documenting the geographic variation in the take-up of the EITC, the knowledge generated by word of mouth can lead to significant heterogeneity in behavior adoption. This mechanism is made explicit by Alstadsæter *et al.* (2019) and Drago *et al.* (2020), who document that taxpayers affect each other's decisions about tax avoidance. In particular, Drago *et al.* (2020) find that neighbors of those who received a letter addressing their tax reporting are more likely to switch from evasion to compliance than households living in neighborhoods where no one received such a letter. These findings highlight the fact that individuals form beliefs about their own detection probability using even fragmented

[6] Similarly on the corporate taxation side, Bohne and Nimczik (2018) find that tax avoidance behaviors follow managers and tax experts as they transfer between firms. Pomeranz (2015) finds that after a firm is audited, tax compliance also improves among that firm's suppliers.

information about aggregate audit rates, such as observing a neighbor receiving a tax-related letter, profoundly shaping personal perceptions of audit risk. This suggests that individuals extrapolate from these isolated instances to infer broader enforcement patterns, thus integrating these observations into their understanding of the likelihood of being audited themselves, which in turn influences their tax compliance decisions.

A similar reasoning can be used to understand how media coverage of specific audits and audit rates can inform a person's perception of audit risk, especially if those audits occur to people with similar characteristics to them. One of those characteristics can be the location where the audited people live. Tauchen, Witte, and Beron (1993) use audit rate variation at IRS-office level on microdata from the IRS Taxpayer Compliance Measurement Program (TCMP)[7] to find that local audit rates stimulate individual compliance.[8] They estimate that the indirect effect of audits is twice the size of the direct effect. The reasoning for using office-level audit rates stems from the fact that back in the 1970s, the period the paper analyzes, IRS district offices conducted the audits and had different staffing levels. Thus, the number of audits they could complete varied across district offices. As a result, some taxpayers were audited or not audited because they filed in districts that were over- or under-staffed in relation to other districts. Therefore, the local audit rate was informative to local taxpayers building their belief about the detection probability they would face. As the IRS budget shrank over time and catalyzed by IRS restructuring in 1998, auditing responsibility shifted from district offices to a centralized system heavily reliant on correspondence audits. Hence, since the 2000s taxpayers' audit rate references are largely national instead of local.

3 Data

Our methodology relies on modeling individual level compliance as a function of IRS audit rates, while controlling for other drivers of compliance. Our primary compliance measure is derived from National Research Program (NRP) microdata. NRP selects a stratified random sample of individual income tax returns for examination for a given tax year. Because the NRP sample is designed to be representative of the population, audits through the NRP examine taxpayers who might not have been examined under normal operational audit procedures. These audits potentially encompass the whole tax return, as opposed to targeting specific areas of noncompliance, as in operational audits. The program provides useful information about noncompliance among the general population and the insights it reveals are used to update operational audit selection procedures, improve resource allocation, and provide estimates of the tax gap (IRS, 2022).

We interpret the behavior of the individuals in the NRP sample as being representative of similar taxpayers in the general population. However, we are interested in the aggregate audit rate faced by the segment of the population represented by the NRP taxpayer—not the audit probability of

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[7] TCMP, a precursor to IRS's NRP, contained detailed information on compliance (resulting from detailed audits) for a stratified random sample from the population.

[8] On the corporate side, Hoopes, Mescall and Pitman (2012) take a similar approach and find that doubling the audit rate increases effective tax rates by 7 percent. Notably, they survey corporate tax executives and find that many take note of historical audit rates.

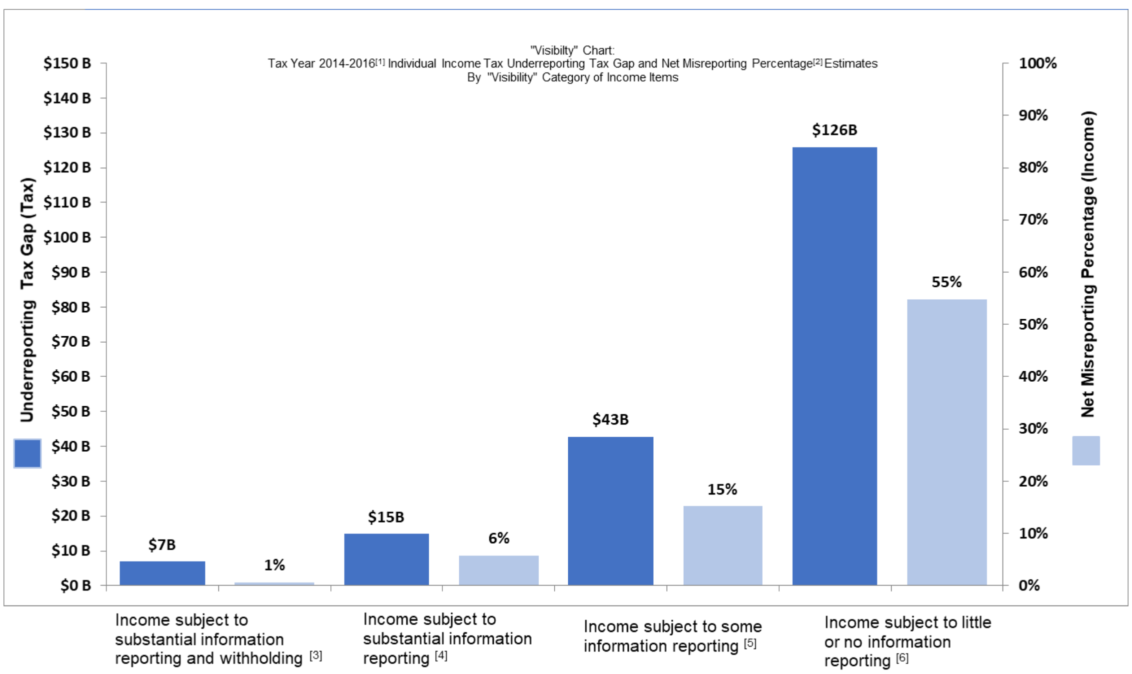
the taxpayer in the NRP sample. Audit rates are constructed by aggregating IRS enforcement data according to the audit categories employed by both NRP and operational audits.

3.1 Dependent Variables

We select all returns audited through the NRP for TYs 2006-2014.[9] For each return, we use the reported amounts and NRP-corrected amounts of certain line items. Our primary outcome variable is the net misreported amount (NMA), a concept used throughout tax gap studies (IRS, 2022). It is calculated for a given set of line items as the difference between the correct amounts and reported amounts for each return. We calculate six measures of NMA based on categories of line items at the return level that span different types of income and offsets. For income and tax categories, NMA is calculated as *Corrected Amount – Reported Amount*, and positive NMA values indicate understatements of tax. For offset categories (e.g., offsets to income, such as deductions, and offsets to tax, such as credits), NMA is calculated as *Reported Amount – Corrected Amount*, so that positive NMA values again indicate understatements of tax.

For each return, we compute the NMA for six groups of tax return line items based on how visible they are to the IRS. Four of the line-item groups relate to different types of income (Visibility Groups 1-4), while the remaining two groups combine offsets to income (Visibility Group 5) or offsets to tax (Visibility Group 6). We define visibility as the degree to which income or offsets are subject to withholding and/or third-party information reporting. Compliance on income reporting varies with the "visibility" of the income. Income subject to little or no information, such as sole proprietor income, makes up the largest portion of the underreporting tax gap (IRS, 2022).

Figure 3: Underreporting of Income as a Function of its Visibility to the IRS



Source: Internal Revenue Service (2022)

[9] 2015 NRP data was released at the time of the writing of this report, and we are adding these data to our sample in ongoing work.

Visibility Group 1 is the income category subject to the most information reporting and withholding while Visibility Group 4 is subject to the least. We hypothesize that compliance on certain line items may be more responsive to IRS audit rates than others. For example, rising audit rates may induce taxpayers to more accurately report line items that would be typically targeted by an audit – items that have substantial, limited or even low visibility. It is unclear whether taxpayers change their compliance behavior on high visibility line items that are usually handled by automated document matching programs rather than by audits. It is also unclear whether taxpayers change compliance on items with *no* information reporting since such income can be difficult to validate through audits. In our analysis, we evaluate each NMA measure as the dependent variable in separate analyses.

Each of the six NMA measures are relevant only to certain taxpayers, depending on their tax situation. For each visibility group regression, we remove taxpayers who report zero amount *and* have zero true (corrected) amount on any of the line items in the visibility group. This ensures that a zero NMA value corresponds to compliance behavior and not to irrelevance of line items for the given taxpayer.

Table 2. Visibility Group Definitions

Visibility Group	Category	Line Items Included	Visibility
1	Income	Wages & Salaries	**High:** subject to substantial information reporting and withholding
2	Income	Pensions and annuities, unemployment compensation, dividend income, interest income, state income tax refunds, and taxable social security	**Substantial:** subject to substantial information reporting
3	Income	Partnerships/S corp. income, capital gains, and alimony income	**Limited:** subject to some information reporting
4	Income	Nonfarm proprietor income, other income, rents and royalties, farm income, and form 4797 income	**Low:** subject to little or no information reporting
5	Offsets to income	Adjustments, deductions, and exemptions	**Mixed:** subject to varying amounts of information reporting
6	Offsets to tax	Refundable and nonrefundable credits	**Mixed:** subject to varying amounts of information reporting

3.2 Independent Variables

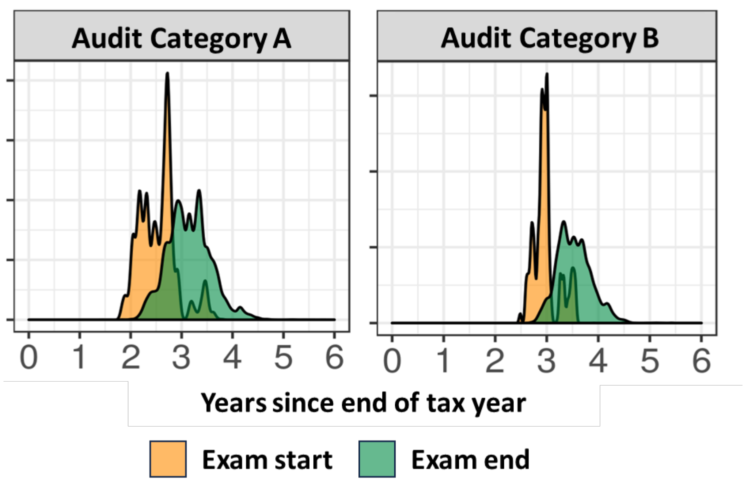
3.2.1 Audit Rates

The primary regressors of interest are audit rates. We construct the audit rate for a given tax year from IRS enforcement data as the number of unique tax returns from that tax year that were audited divided by the total number of unique returns filed for that year. We also create separate audit rates for different groupings of taxpayers based on TPI level, the filing of certain schedules (like Schedule C for nonfarm sole proprietors and Schedule F for farm sole proprietors) and EITC claiming. These groupings of individual tax returns – known as "activity codes" – are listed in Table 7 of the Appendix. As the third column of Table 7 shows, most of the taxpayer population has modest annual income (below $200,000) and no active business income or expenses (Activity Codes 272 and 273).

It is important to note that our dependent variable and other control variables are specified at the return level, but our primary variable of interest – audit rates – is specified at the group level. Each observation in our NRP sample is assigned the audit rate for that return's activity code – reflecting the likelihood that taxpayers are most responsive to audits of similarly situated taxpayers (e.g., with similar types and amounts of income and offsets).

The second methodological decision we made about the audit rate variable was to specify a two-year lag of audit rate in the regressions. The choice to lag the audit rate arises from the natural delay in enforcement processing time. Figure 4 provides an example of the distribution of audit start and audit closure dates relative to the filing year of the audited return, for two categories of audit. For many audit categories, an audit begins 2-3 years and closes 2-4 years after the filing year of the audited return. For example, a return for income earned in TY2010 would be filed in spring 2011. If selected for audit, the taxpayer might be notified in late 2012. In spring 2013, the taxpayer will file the TY2012 return. Thus, the audit rate pertaining to TY2010 returns is the most recent information the taxpayer will have on IRS enforcement levels when filing the TY2012 return – motivating a two-year lag on audit rate in our regressions.

Figure 4: Distribution of Audit Start and Closure for Two Categories of Audit



3.2.2 Control Variables

For each NRP return, our control variables are constructed from tax characteristics that may help explain compliance behavior. These include filing status (whether the taxpayer filed as Married Filing Jointly), the total exemptions claimed by the taxpayer, the presence of wage income, the claiming of the child tax credit, whether the taxpayer itemized deductions, whether mortgage interest was deducted, an indicator for taxpayers over 65 years of age, whether the taxpayer used a paid preparer, and an indicator for electronic filing. We base these variables on the taxpayer's reported information on their return.

We also control for the correct amount on the return corresponding to the NMA variable of interest. For example, when Visibility Group 6 (credits) NMA is the dependent variable, we include the correct amount of credits as the regressor. This construction allows us to model changes in NMA that arise from compliance behavior and not from changes in the underlying true tax, income, or offsets.

3.3 Data Summary

Figure 5 summarizes sample size by activity code. We remove outliers by trimming the bottom and top five percent from the distribution of total reported income in each activity code, since there are outliers in terms of high income and negative income. This trimming affects the entire NRP sample, regardless of visibility group. Within each visibility group regression, we remove observations with negative NMAs. Negative NMAs imply overstating of income or underclaiming of offsets, and in this paper, we focus on focus on noncompliance in the other direction (which is more common). Except for Activity Code 271, our sample includes at least 4,000 returns for each activity code during TYs 2006-2014.

Figure 5. Counts of NRP Returns Before and After Trimming (TYs 2006-2014)

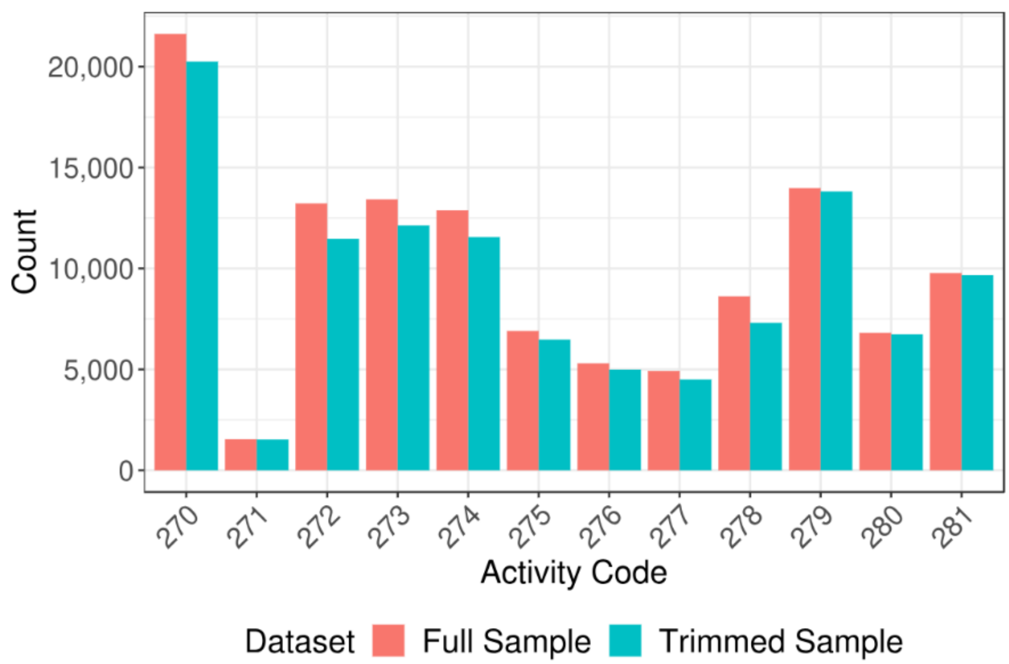
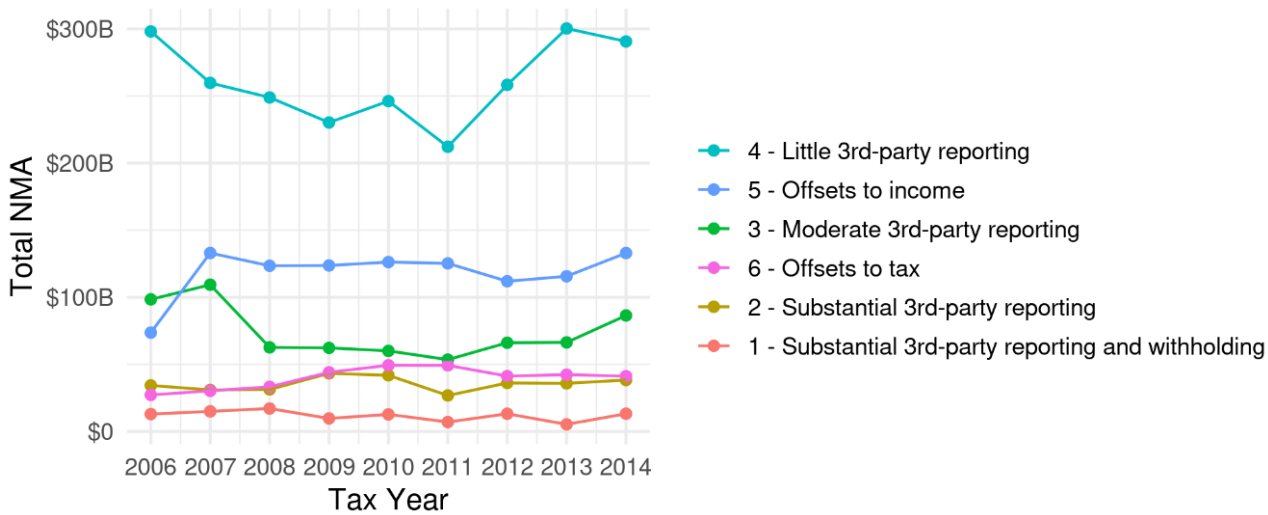


Figure 7 summarizes the aggregate NMA over time by visibility group. The total NMA for each visibility group is calculated by weighting each return-level NMA in our NRP sample (using NRP sampling weights) and summing across all returns. The largest source of noncompliance is from Visibility Group 4, income line items with little or no information reporting (such as nonfarm proprietor income and rents and royalties income). Aggregate NMA in this group fell and then increased over time. The totals for Visibility Groups 3 and 5 fell and plateaued somewhat.

Figure 7. Aggregate NMA* over Time, by Visibility Group (Weighted)



* The NMA for groups 1-4 represent understated income, while the NMA for group 5 represents overstatements of income offsets and the NMA for group 6 represents overstatements of tax credits.

Figure 8 disaggregates NMA totals by activity code. Certain types of taxpayers are more likely to have certain types of income and offsets and are thus more likely to contribute to NMA on those items. For example, Activity Code 270 makes up a large portion of misreporting on credits (Visibility Group 6) but a much smaller portion of misreporting on partnership/S corporation income, capital gains and alimony income (Visibility Group 3). Activity Codes 279-281, despite comprising only 3.7 percent of the population (per Table 7), contribute almost 25 percent of misreporting on Visibility Group 3 income. Activity Code 272, which includes over 55 percent of the population, contributes the largest portion of misreporting in Visibility Groups 1 and 2 but much less for 3 and 4.

Figure 8. Aggregate NMA by Activity Code (Weighted)

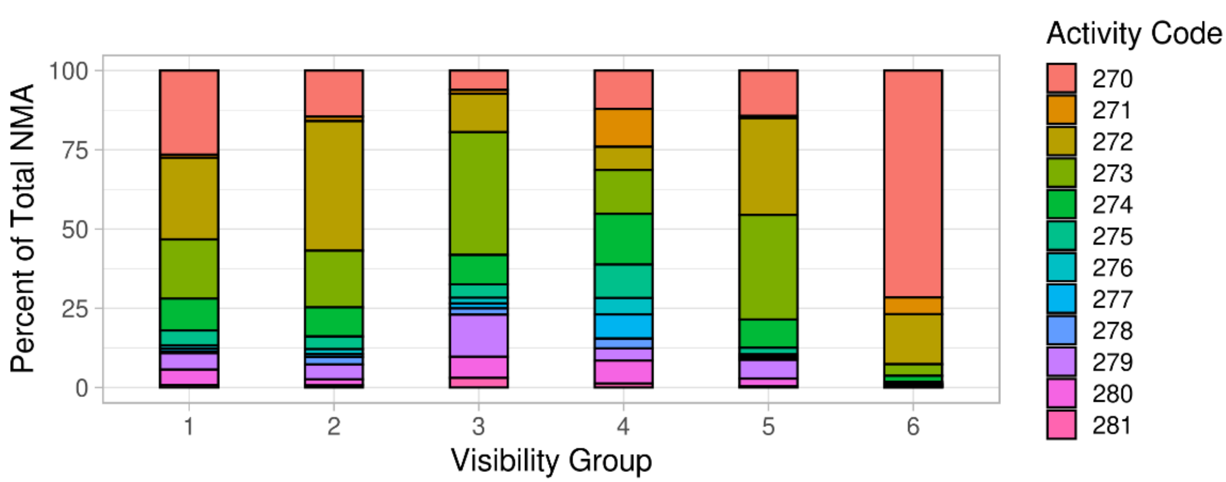


Table 3 summarizes the dependent and independent variables in our model (excluding audit rates) by Tax Year. These summary statistics apply to our trimmed data, and observations are weighted by NRP sampling weights. Dollar-denominated variables (NMAs and Correct Amounts) are adjusted to 2018 dollars. For the average return in our sample, NMA drops slightly then increases during this time for most visibility groups. Correct amounts of Visibility Group 1, 3 and 4 income also drop slightly then increase during this time. Commensurate with decreasing marriage rates and our aging population, the proportion of NRP taxpayers filing as Single/other status increases somewhat, as does the proportion of taxpayers over 65. Variables declining during this time are the proportion of taxpayers with wage income, claiming a child tax credit, itemizing, and deducting mortgage interest. The use of a paid preparer fell over time, while electronic filing rose dramatically until 2012 then slightly declined.

Table 3. Weighted Average Statistics for NRP Sample by Tax Year

Variable	2006	2007	2008	2009	2010	2011	2012	2013	2014
Dependent Variable (NMA)									
Visibility Group 1	$157	$175	$189	$107	$140	$78	$144	$57	$143
Visibility Group 2	$416	$363	$347	$478	$462	$300	$395	$387	$416
Visibility Group 3	$1,194	$1,283	$695	$688	$663	$600	$723	$717	$938
Visibility Group 4	$3,617	$3,048	$2,762	$2,544	$2,720	$2,379	$2,827	$3,247	$3,156
Visibility Group 5	$893	$1,561	$1,370	$1,367	$1,395	$1,404	$1,225	$1,250	$1,443
Visibility Group 6	$330	$355	$369	$487	$545	$552	$451	$457	$447
Independent Variables									
Correct Amount									
Visibility Group 1	$52,400	$52,745	$50,424	$49,944	$48,948	$47,822	$50,503	$49,492	$50,665
Visibility Group 2	$9,715	$10,367	$9,745	$9,836	$10,191	$9,972	$9,728	$9,697	$10,141
Visibility Group 3	$10,290	$10,028	$6,477	$5,009	$6,135	$6,507	$8,382	$8,008	$9,623
Visibility Group 4	$11,556	$10,538	$9,613	$8,680	$9,770	$9,467	$11,211	$11,308	$11,846
Visibility Group 5	$18,495	$18,005	$17,431	$17,023	$16,528	$15,965	$16,250	$15,990	$15,803
Visibility Group 6	$1,091	$1,059	$1,221	$1,316	$1,213	$1,126	$1,116	$1,100	$1,149
Filing Status									
Single/other	57%	58%	57%	57%	59%	60%	60%	61%	60%
Married filing jointly	43%	42%	43%	43%	41%	40%	40%	39%	40%
Total Exemptions									
0 or NA	2%	1%	2%	2%	2%	2%	2%	2%	2%
1	32%	31%	31%	33%	33%	33%	34%	34%	35%
2	32%	33%	31%	32%	32%	32%	31%	32%	28%
3	17%	17%	17%	15%	16%	15%	15%	15%	16%
4	12%	11%	12%	12%	11%	11%	12%	11%	12%
5+	6%	7%	7%	6%	6%	6%	7%	6%	7%
Had wage income	85%	85%	85%	85%	84%	83%	85%	83%	83%
Claimed child tax credit	24%	23%	23%	21%	22%	19%	19%	19%	19%
Itemized	46%	46%	41%	39%	41%	40%	40%	39%	38%
Deducted mortgage interest	36%	37%	33%	31%	32%	30%	30%	29%	27%
Over 65	12%	13%	14%	14%	13%	13%	14%	15%	15%
Used paid preparer	66%	66%	65%	62%	63%	62%	62%	62%	59%
Filed electronically	50%	65%	71%	73%	80%	84%	84%	70%	70%

Note: These summary statistics apply to our trimmed NRP sample. Statistics are weighted by NRP sampling weights. Means are displayed for NMAs and Correct amounts, while proportions are displayed for all other variables. Dollar-denominated variables are expressed in terms of 2018 dollars.

4 Methods

Our baseline specification models taxpayer *i*'s compliance in tax year *t* as a function of IRS enforcement and other drivers of compliance:[10]

$$NMA_{it} = \beta_0 + \beta_1 Audit\ Rate_{g,t-2} + \beta_2 Correct\ Amount_{it} + \boldsymbol{\beta Taxpayer\ Controls_{it}} + \boldsymbol{\delta Activity\ Code_g} + \varepsilon_{it} \quad (1)$$

We run a separate regression for each visibility group. Return-level NMA on those line items is our main dependent variable. Since there is skewness in NMA, we winsorize NMAs to the 95th percentile. Audit rate is the primary variable of interest. As discussed previously, each taxpayer is assigned the audit rate for their activity code group *g* for the tax year in question. We lag the audit rate by two years to reflect the delay in enforcement processing time. We hypothesize that β_1 will be negative—a decrease in audit rates should lead to an increase in noncompliance.

Importantly, we control for the correct amount that should have been reported on the line items in question, for each visibility group; this is presumably the most important determinant of what is actually reported, and therefore the NMA. Additional taxpayer control variables refer to the variables described in Section 3.2.2. We include fixed effects for activity code. These capture time-invariant determinants of compliance that are unique to each activity code, unrelated to audit rate changes. We do not include tax year fixed effects in our regressions due to our reliance on variation over time to identify the audit rate effects.[11] Finally, all regressions are weighted by NRP sampling weights.

Our econometric approach is most similar to Tauchen, Witte, and Beron (1993) and Hoopes, Mescall, and Pitman (2012), who evaluate the effect of aggregate audit rates on compliance at the micro level (while controlling for auditor assessed income or proxies thereof). One difference from their approach is that we use lagged audit rates instead of contemporaneous ones. While a contemporaneous audit rate reflects audit probability for the return being filed, it is unlikely that the taxpayer knows the contemporaneous audit rate or their audit probability until the audit cycle for that year has completed. Rather, they are more likely to be aware of historical audit rates. To the extent that audit rates change over time (which they have), contemporaneous audit rates are not a suitable replacement for historical ones.

Another departure from Tauchen, *et al.* (1993) and Hoopes, *et al.* (2012) is in the treatment of the audit rates econometrically. They use an instrumental variable approach, but we don't for two reasons. First, lagged audit rates do not suffer from reverse causality, as taxpayers cannot influence past audit rates through current reporting behavior and IRS cannot influence past compliance behavior through current audits. Second, audit rates have generally declined across the board at varying rates due to declining resources and shifts in allocation (but not in response to improved compliance), thereby creating a natural experiment for evaluating the causal effect of audit rates.

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[10] Since NRP samples are independent each year, our data are pooled cross-sections rather than panel/longitudinal.

[11] Our model controls for tax law changes through the correct amount, but it does not control for any tax policy changes that are specific to certain taxpayer groups, such as through the inclusion of activity code-tax year fixed effects. Such effects would be collinear with our audit rate variables, which do not vary within an activity code and tax year. In future work, we hope to include variables capturing known policy changes for certain activity codes.

5 Results

In this section, we present the results of estimating Equation (1), focusing on the main findings related to the audit rate variable. We then translate the estimated impacts on line-item reporting into impacts on revenue using a tax calculator. Finally, we combine revenue with cost data to calculate the final return on investment of IRS enforcement during this time period.

5.1 Regression Results

Table 4 presents our regression results. The number of observations for each regression varies due to the trimming of negative NMAs and "irrelevant" taxpayers (zero reported and zero true amount) for each visibility group. Smaller sample sizes affect statistical power and may be responsible for the lack of statistical significance on the audit rate variable for Visibility Group 3.

Audit rates have the expected negative effect on noncompliance for all visibility groups except for Group 1, which shows a small positive effect (not statistically significant).[12] This aligns with our hypothesis that the effect of audit rate variation is likely small or zero, given this line item is mostly validated by automated matching programs. For Visibility Group 2, a one percentage point increase in audit rates decreases noncompliance on a return by $139. This is a modest but statistically significant effect. This group includes taxpayers such as retirees with pensions/annuities income and taxpayers between jobs receiving unemployment income.

For Visibility Group 3, a one percentage point increase in audit rates decreases noncompliance on a return by $694, but this effect is not statistically significant. However, this regression was conducted on the smallest sample size. This income group includes partnership/S corporation income, capital gains, and alimony income—sources of income with some limited information reporting. These types of income are often the targets of audits, and it is likely that the lack of statistical significance arises from sample size issues rather than from no meaningful effect.

For Visibility Group 4, a one percentage point increase in audit rates decreases noncompliance on a return by $806 – the largest effect across all visibility groups and is statistically significant. Income in this group is subject to very little information reporting – such as nonfarm proprietor income, rents and royalties, farm income, and form 4797 income. This is also the visibility group with the largest amount of noncompliance (see Figure 3) and thus more room for improvement in compliance if audit rates were to rise.

Finally, audit rates have the expected effect on adjustments, deductions, exemptions, and credits (Visibility Groups 5 and 6). A one percentage point increase in audit rates decreases noncompliance on adjustments, deductions, and exemptions by $80 per return (not statistically significant) and on refundable and nonrefundable credits by $64 per return (statistically significant).

[12] The result for Visibility Group 1 is consistent with a separate analysis we conducted using Automated Underreporter (AUR) data (results are not included here for conciseness) among a sample of tax returns taken from the entire population. AUR matches third-party information documents sent to the IRS with what taxpayers report on their tax returns. This screens for noncompliance on line items with substantial information reporting, such as wages and salaries. We construct a measure of NMA based on AUR-corrected line items. While NRP-adjusted NMA is available only for NRP audits, AUR-adjusted NMA is available for all taxpayers using third-party information documents. This approach allows us to evaluate a sample of taxpayers outside the standard NRP population for this analysis.

Table 4. Regression Results†

	Dependent Variable: NMA					
	Visibility Group 1	Visibility Group 2	Visibility Group 3	Visibility Group 4	Visibility Group 5	Visibility Group 6
Audit Rate (2 Year Lag)	**14.07**	**-139.06 *****	**-694.26**	**-806.28 ***	**-80.58**	**-63.09 *****
	46.65	**53.32**	**510.80**	**488.40**	**103.29**	**10.53**
Correct Amount	0.001 ***	0.008 ***	0.003 ***	0.016 ***	-0.024 ***	-0.0004 ***
	0.000	0.000	0.000	0.000	0.001	0.000
Total Exemptions 1	-82.66	4.27	1,758.35	5,013.89 **	222.30	-44.04
	112.69	138.38	1,223.25	2,031.73	264.20	99.14
Total Exemptions 2	-208.98 *	87.31	3,155.59 **	6,420.07 ***	1,553.30 ***	308.48 ***
	119.70	148.56	1,429.04	2,166.77	282.88	99.60
Total Exemptions 3	-273.54 **	98.29	3,903.88 **	6,279.30 ***	1,981.16 ***	536.63 ***
	126.39	157.52	1,530.01	2,252.24	299.75	100.16
Total Exemptions 4	-299.91 **	168.35	3,387.64 **	6,912.06 ***	1,860.49 ***	609.14 ***
	133.92	164.74	1,599.40	2,338.20	319.44	100.83
Total Exemptions 5+	-158.58	345.84 **	4,818.52 ***	7,831.20 ***	2,271.76 ***	704.55 ***
	141.66	173.54	1,689.29	2,435.90	339.74	101.47
Wage Income		218.58 ***	-988.15 **	-3,383.41 ***	285.10 **	67.89 ***
		54.40	482.67	633.11	133.99	19.52
Claimed child tax credit	41.23	-262.04 ***	-882.18	-2,958.06 ***	-313.95 **	-110.79 ***
	49.96	59.51	676.53	819.15	125.75	13.20
Itemized	-139.96 *	-156.35 ***	-656.25	2,399.92 ***	2,869.74 ***	3.10
	73.59	60.44	550.10	886.61	157.75	22.67
Deducted mortgage int.	30.23	192.29 ***	881.68	-2,028.66 **	-741.34 ***	-51.24 **
	72.57	59.68	549.61	888.76	160.72	22.51
Over 65	-182.10 **	361.39 ***	-1,232.10 **	-4,639.70 ***	-187.20	52.60 **
	76.122	55.306	510.240	759.367	147.722	23.007
Used paid preparer	132.68 ***	-4.05	747.70 *	957.22 *	-280.53 ***	69.49 ***
	36.91	38.86	422.47	573.40	88.84	11.12
Filed electronically	81.36 **	-90.49 **	-1,099.77 ***	-1,616.72 ***	75.57	7.15
	40.48	39.19	382.35	535.43	93.87	11.98
Married-Joint Status	63.30	32.21	-1,711.42 **	-12.72	-1,590.65 ***	-410.54 ***
	54.97	66.04	829.94	896.88	132.89	15.35
Constant	246.38 *	365.29 **	5,425.60 ***	3,883.68	-155.02	227.57 **
	147.27	185.29	1,841.59	2,373.13	360.45	102.18
Observations	91,569	83,897	55,908	77,393	118,991	64,190
Tax Year Fixed effect	N	N	N	N	N	N
Adjusted R^2	0.001	0.027	0.009	0.04	0.022	0.047
F Statistic	4.072 ***	92.130 ***	20.887 ***	126.071 ***	104.359 ***	122.403 ***
Degrees of Freedom	91,479	83,847	55,864	77,331	118,867	64,132

† Standard errors on second line. Statistical significance: *** 1% ** 5% * 10%

5.2 Translating Changes in Line-Item Misreporting into Changes in Revenue

The coefficients on the audit rate variable in Table 4 describe the impact of a change in audit rate on dollars of misreporting (i.e., NMA). We translate the impact on reporting compliance into the impact on tax revenue. Mechanically, this first involves taking the change in dollars of misreporting for the entire visibility group (derived from the regression coefficient and the actual change in audit rate) and allocating these changes to individual line items within the visibility group. This allocation was done in proportion to how the detected NMAs were distributed across line items within the visibility group on the original return – reflecting the assumption that the rate of change in misreporting is the same for each line item in the category. Further, we ensure these allocations are subject to the tax rules governing each line item. This process is especially important for offset line items, which often are subject to different limitations than other items in the same visibility group.

Table 5 illustrates how a hypothetical audit rate decline affects a hypothetical tax return. Columns 5 and 6 show the detected amount of NMA (from the NRP audit) and the reported amount from the NRP return. These "actuals" are the implied result of an audit rate decline two years prior (in this example). In columns 3 and 4, we calculate the counterfactual amount reported and the corresponding NMA had the audit rate *not* declined. The last column shows the difference between the actual and the counterfactual amounts – this is the impact on this return of the decline in audit rate.

For example, no NMA was detected on wages and salaries for the hypothetical return in Table 5 – so the counterfactual NMA remains zero due to our allocation rules. However, there was $150 of misreporting detected on interest and dividend income. This detected amount was the result of an audit rate decline in this example – so the counterfactual misreported amount ($100) is lower. Likewise, the counterfactual misreported amounts are lower for all line items that had a detected NMA on this hypothetical return. Lower NMAs in turn result in higher counterfactual income and lower offsets.

Once NMA changes are allocated to individual line items, we feed the counterfactual tax return through a tax calculator to determine the tax liability that would have been reported on the NRP return had the audit not changed. The bottom right box (in yellow) shows the overall impact on tax after refundable credits (TARC) – this taxpayer would have paid $552 more in TARC had audit rates not declined two years prior. Finally, we apply this approach to each NRP return and apply NRP weights to calculate population-level revenue impacts of the audit rate changes.

Table 5. Illustrative Impact of a Hypothetical Audit Rate Decline on Tax Paid by a Hypothetical Taxpayer

Visibility	Line Item	$ Reported w/o decline	NMA w/o decline	Detected NMA	Observed Return	Δ
1 High	Wages & Salaries	$60,000	$0	$0	$60,000	$0
2 Substantial	Pensions & annuities					
	Unemployment compensation					
	Interest & dividend income	$2,500	$100	$150	$2,450	-$50
	State income tax refunds	$500	$0	$0	$500	$0
	Taxable social security benefits					
3 Limited	Partnership / S corp. income					
	Trust income					
	Capital gains	$3,000	$160	$200	$2,960	-$40
	Alimony income	$100	$400	$500	$0	-$100
4 Low / No	Nonfarm proprietor income	$70,000	$10,000	$11,000	$69,000	-$1,000
	Farm income					
	Rents & royalties	$50,000	$4,545	$5,000	$49,545	-$455
	Form 4797 & Other income					
	Total Income	**$186,100**	**$15,205**	**$16,850**	**$184,455**	**-$1,645**
5 Income Offsets	Adjustments					
	Exemptions	$8,000	$0	$0	$8,000	$0
	Deductions	$20,000	$3,000	$3,150	$20,150	$150
	Tentative tax	**$31,515**	**$5,098**	**$5,600**	**$31,013**	**-$502**
6 Tax Offsets	Nonrefundable credits	$2,600	$100	$150	$2,650	$50
	Refundable credits					
	Tax after refundable credits (TARC)	**$28,915**	**$5,198**	**$5,750**	**$28,363**	**-$552**

5.3 Calculating Return on Investment

The final step of our analysis is to calculate return on investment (ROI). We combine the revenue estimates from the prior section with data on enforcement costs. We use IRS records to calculate the cost of audits corresponding to the audit rates used in Equation (1). We include costs associated with the Exam, Appeals, Counsel, and Collection functions. It is important to note that aggregate audit costs generally move in the same direction as audit rates, with a few exceptions that likely arise from productivity changes (such as from a different mix of auditor experience or levels year over year). We remove these handful of year-activity code observations where this is the case.

Table 6 summarizes the direct ROI, general indirect ROI, and combined ROI for four groupings of taxpayers based on TPI. Direct ROI is calculated from audit records and includes only the additional tax actually paid as a result of the audit for the tax year that was audited. We see that $1 of enforcement cost during this 2006-2014 time period generated $3.30 of direct revenue on average and almost $9 when applied to audits of taxpayers earning $400k and above. The general indirect ROI shown is calculated from this paper's analysis and shows the population-level impact of a dollar of auditing cost. We provide a range of general indirect ROIs depending on whether we use all point estimates from Table 4 (high end) or only statistically significant estimates (low end). $1 of enforcement cost generates around $10-$13 of general indirect revenue, with larger impacts on taxpayers earning between $200k-$400k.[13] Finally, combined ROI shows the total impact of a dollar of enforcement. $1 of enforcement costs generates, on average, roughly $13-16 of total revenue when considering direct and indirect effects. (Note that the variation in these ROIs across the TPI ranges is not directly applicable to IRS resource allocation decisions, which should be made on the basis of the cost-effectiveness of the next enforcement case. In contrast, the direct ROIs here are *averages* (total revenue divided by total cost) and the indirect ROIs are *average marginals* (the change in revenue divided by the change in cost. Nonetheless it seems likely that taking indirect effects into account would change the mix of enforcement allocations to the various categories.)

Finally, we calculate the implied revenue loss from the audit rate declines observed from 2009 to 2012. Although this decline resulted in a $211M savings in enforcement costs, it led to an estimated loss of almost $2.2B in voluntary tax revenue from 2011 to 2014.[14]

Table 6. Return on Investment of IRS Individual Income Tax Audits, Tax Years 2006-2014

Return Total Positive Income	Direct ROI	General Indirect ROI	Combined ROI
< $100K	2.0	5.7 - 6.2	7.7 - 8.2
$100K to under $200K	2.8	9.4 - 14.1	12.2 - 16.9
$200K to under $400K	3.1	15.0 - 22.3	18.1 - 25.4
$400K and over	8.9	7.8 - 12.4	16.7 - 21.3
All Groups	**3.3**	**9.6 - 13.1**	**12.9 - 16.4**

6 Discussion

While most research on the impact of IRS enforcement on overall tax compliance evaluates specific local networks, this paper contributes to a small literature on the "comprehensive" general indirect effects of IRS enforcement. We aim to capture the effects on the entire taxpayer population of all IRS individual income tax audits, regardless of the channels through which the impacts propagate throughout the population. As such, these effects are relevant for IRS budget justification, which currently cites the ROI of enforcement on direct revenue and does not quantify overall indirect effects (IRS, 2024).

We advance understanding of the nature and magnitude of comprehensive indirect effects by implementing several novel or rarely used approaches. Ours is one of the few papers in this area

[13] Note that our ROI numerator uses tax amounts based on NMAs as recommended by the NRP auditors, while the ROI denominator is the full life-cycle cost of the audits (i.e., not just the Examination cost, but also the cost of any Appeals, Chief Counsel, and Collection activity to assess and collect the tax due). This "apples vs. oranges" ratio yields a lower bound compared with an alternative of using only the Exam cost in the denominator. Alternatively, if we projected the recommended amount to corresponding dollars collected, the ROI would go down, but it wouldn't take into account changes in *undetected* NMAs, which are not observable. So, our ROI definition seems to reflect the best available balance of being conservative yet realistic.

[14] The net average marginal ROI of 10.3 is less than 13.1 because of offsetting increases in audit rates in some activity codes and years.

to use microdata. This allows for more nuanced modeling of taxpayer behavior and the ability to control for return-level characteristics. Departing from prior papers, we use lagged audit rates to proxy for knowledge of IRS enforcement levels. While audit rates for the tax year at hand reflect the true aggregate probability of audit, taxpayers (and their accountants) can plausibly know only past audit rates. Additionally, using lagged audit rates solves the reverse causality (endogeneity) problem; an earlier audit rate is not impacted by this year's compliance, for example.

We find that the indirect effect of audits varies across tax return line items. The effect is larger for items subject to less third-party information reporting and for items with large existing noncompliance. These results are intuitive. High visibility line items such as wages and salaries are screened by automated underreporter (document matching) programs, and misreporting on these line items may be less sensitive to audit rates per se. On the other hand, misreporting on line items *not* validated by simple document matching should be more responsive to the enforcement actions, such as audits, that focus on those line items.

Our top-level finding is that IRS audits of individual income tax returns had a combined ROI of 13:1 to 16:1 during the 2006 to 2014 Tax Years. Put another way, the general indirect effect was 3 to 4 times larger than the direct effect. This is in line with prior studies (see Table 1) and slightly on the lower end of the range of prior estimates. These results can be used to understand how historical IRS budget cuts have impacted voluntary compliance and how new IRS funding (such as through the Inflation Reduction Act) present an opportunity to reverse that trend.

6.1 Limitations and Future Research

It is important to remember that this study is focused solely on the reporting noncompliance behavior detected on individual income tax returns, which is the largest component of IRS tax gap estimates (IRS, 2022); it does not address the nonfiling or underpayment components of the tax gap, nor does it encompass other types of tax. Because of this focus, the only IRS enforcement considered so far has been audits of timely filed individual income tax returns.

Another limitation of this research is that NRP audits may not detect all noncompliance among taxpayers with high and unreported income. This will impact the accuracy of our dependent variable. Prior research has attempted to shed light on previously undetected offshore accounts and passthrough income (Guyton *et al.*, 2021) but has not explored its relation to changes in compliance over time.

Moreover, our estimates relate just to the specific time period studied and may not be directly generalizable to the present. This is because the relationship between audit rates and taxpayer behavior in the general population seems to be highly dependent on things like: the distribution of audit resources across the various categories of tax returns; the distribution of income, deductions, and tax credits across tax returns; the extent to which other factors influence taxpayer behavior; and the tax law in place in a given year. Although it is likely that the general indirect effect today is similar to what we have estimated for the 2006 to 2014 time period, our estimates are not a universal constant.

There are several near-term extensions we plan to address. We plan to deepen the theoretical motivation for the audit rate variable and potentially change its specification to improve causal linkages and introduce more variation. This could be done, for example, by deriving audit rates for population sub-strata beyond Activity Code. We also hope to increase statistical power through other means. NRP samples are limited in size (and have been declining in recent years), affecting our ability to derive precise estimates. A potential alternative to using NRP data directly is to impute compliance measures from NRP to the universe of tax returns. Although this would greatly improve sample size, proper validation would need to be conducted to ensure compliance imputations are reliable.

Finally, the ultimate goal of this research is to support IRS budget justifications by estimating the ROI of all IRS activities. IRS service, outreach, education, and IT investments plausibly have an impact on compliance, as well. These IRS services help taxpayers become more informed and better equipped to report and pay their taxes correctly at the outset. To account for this, we hope to incorporate into future iterations of this work measures such as IRS website hits and level of service. Although we focus on individual taxpayers in this paper, prior research indicates that corporations track IRS enforcement activities in their accounting practices (Hoopes, Mescall, and Pitman, 2012). Estimating the indirect effect of enforcement on corporate voluntary compliance is another area of future work.

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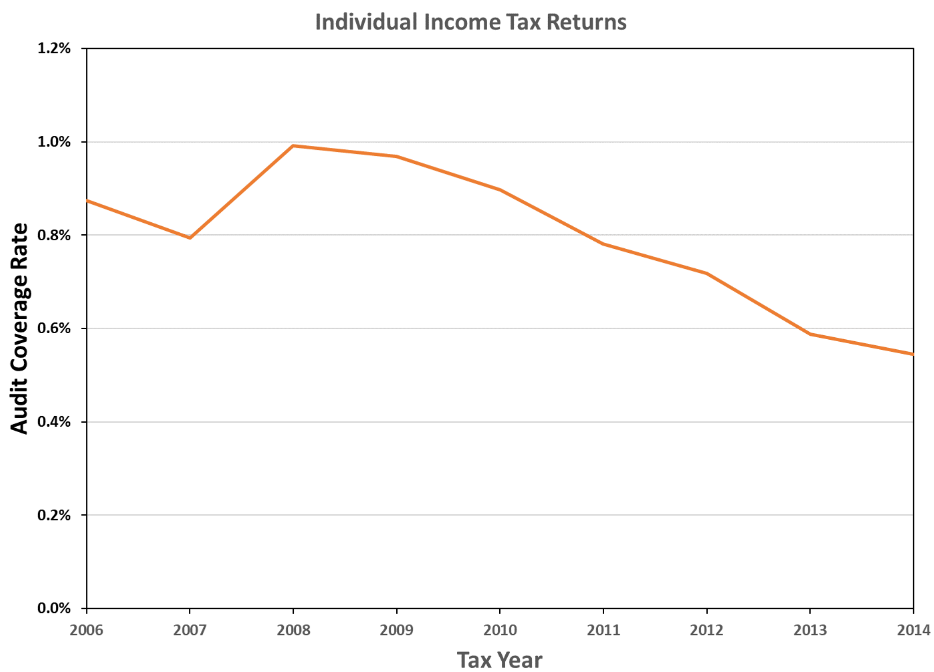
8 Appendix

Figure 4. Audit Coverage* Trend Among Individual Income Tax Returns, TYs 2006-2014



Note: Plots the overall decline in audit coverage among individual income tax returns during Tax Years (TYs) 2006-2014.* *Coverage rate = (number of returns audited) / (total number of returns filed) for the tax year*

Table 7. IRS Examination Activity Code Definitions

Activity Code	Description	Percent of Population	Group
270	EITC present & TPI < $200,000 and Schedule C/F TGR < $25,000 or EITC w/o Sch C/F (As of TY 2008)	17.1%	EITC
271	EITC present & TPI < $200,000 and Sch C/F TGR > $24,999 (As of TY 2008)	1.2%	EITC
272	TPI < $200,000, no Sch C, E, F, or Form 2106 (As of TY 2008)	55.3%	Non-Business Mid-Income
273	TPI < $200,000 and Sch E or Form 2106, no Sch C or F (As of TY 2008)	10.8%	Non-Business Mid-Income
274	Non-Farm Business w/ Sch C/F TGR < $25,000 and TPI < $200,000 (As of TY 2008)	7.3%	Business
275	Non-Farm Business w/ Sch C/F TGR $25,000 - $99,999 and TPI < $200,000 (As of TY 2008)	2.1%	Business
276	Non-Farm Business w/ Sch C/F TGR $100,000 - $199,999 and TPI < $200,000 (As of TY 2008)	0.6%	Business
277	Non-Farm Business w/ Sch C/F TGR > $199,999 and TPI < $200,000 (As of TY 2008)	0.5%	Business
278	Farm Business Not Classified Elsewhere and TPI < $200,000 (As of TY 2008)	0.9%	Business
279	No Sch C or F and TPI > $199,999 and < $1,000,000 (As of TY 2008)	2.4%	Non-Business High-Income
280	Sch C or F present and TPI > $199,999 and < $1,000,000 (As of TY 2008)	1.0%	Business
281	TPI > $999,999 (As of TY 2008)	0.3%	Non-Business High-Income