The Comprehensive General Indirect Effect of Auditing Individual Income Tax Returns*

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Abstract

IRS audit rates have generally fallen for over a decade due to declining resources, impacting direct audit revenues as well as voluntary tax compliance. We contribute to a small literature on the "comprehensive" indirect effects of IRS audits on the general taxpayer population. Using microdata from random audits, we estimate that IRS individual tax audits have a return on investment of 3:1 in direct revenue and between 5:1 and 20:1 in indirect revenue. Estimated ROIs are larger in later years when audit rates declined precipitously, suggesting that steep cuts to IRS budgets have disproportionally more serious consequences than modest cuts.

Keywords: Tax audits, spillovers, general indirect effect, ROI of audits

JEL Codes: H20, H24, H26

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1 Introduction

How much additional revenue could be generated if the Internal Revenue Service (IRS) budget were increased by $X per year? The answer to that question 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, such as audit programs. One impact on overall revenue would come in the form of increased *direct* revenue – additional tax collections resulting from more audits for a particular tax year. Moreover, it is likely that this 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 audit (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 audit (known as the "general indirect effect"). Estimating the spillovers of audits, and thus the full extent of the return to investing in tax audits, 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.[2] Their findings may not be generalizable outside of the specific context or behavioral mechanism studied. Taxpayers may belong to multiple networks simultaneously (e.g., employer networks, professional networks, community networks, etc.), and it is unclear whether the separate impacts of any related network spillovers are additive. Taxpayers may form their perceptions in a more subtle way based on all the factors in their environment.

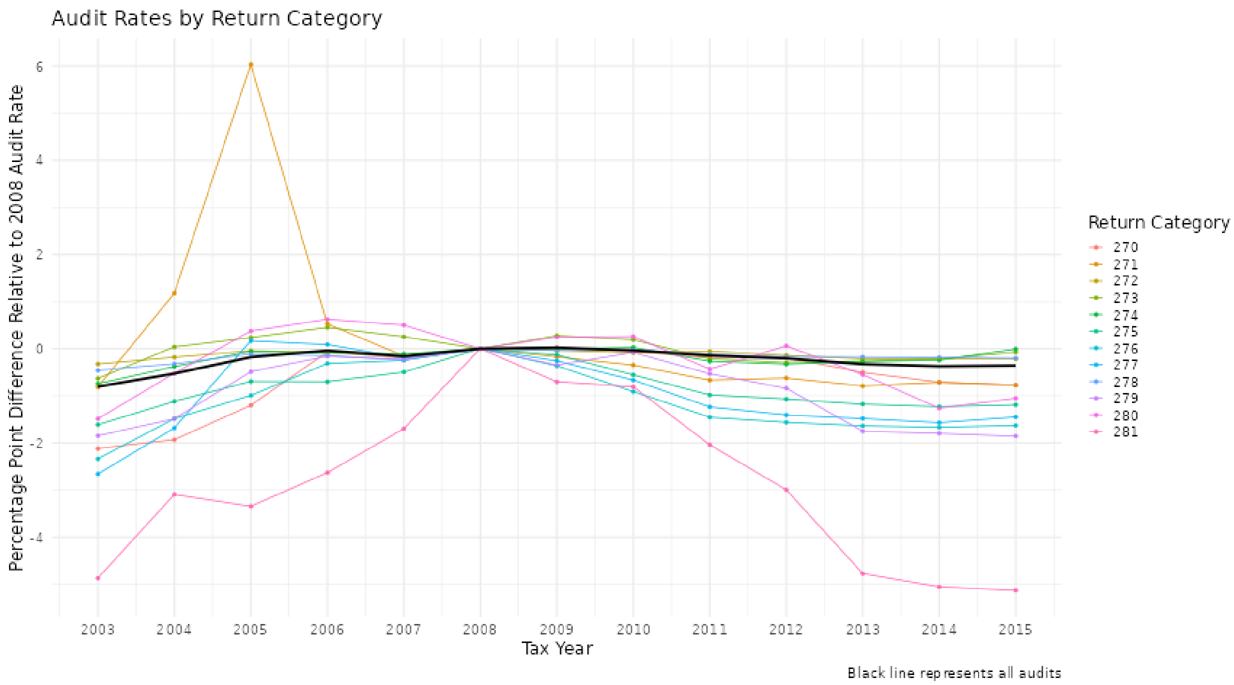
Although local network models lend themselves to theoretical premises and practical experimentation, such narrowly defined analyses do not directly translate into operational applications such as budget justification. To achieve that, the estimated indirect effects should in theory include effects arising: 1) from all IRS audit 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 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 taxpayer behavior in addition to the audit activities in question.

[2] 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.

This paper estimates a comprehensive model[3] 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, the overall individual income tax audit coverage rate has declined substantially from a high of 1% in 2008 to a low of 0.5% in 2014. Figure 1 plots audit rates by return category over time, relative to 2008 as the baseline year. There is an overall trend of increasing audit coverage leading up to 2008 and decreasing coverage thereafter.[4] However, audit rates did not follow a uniform pattern across return categories—IRS' groupings of taxpayers based on Total Positive Income[5] (TPI) level, the filing of certain schedules, and the claiming of the Earned Income Tax Credit (EITC).[6] For instance, while audit rates for most return categories fell by about 50% in the latter half of this period, the audit rate for return category 279 (taxpayers with TPI between $200K and $1M, with no self-employment) fell by almost 80%, while audit rates for return category 274 (taxpayers with TPI below $200K and positive gross revenue from self-employment below $25K) rose by 12%.

[3] The scope of our model is "comprehensive" in that it aims to capture the impacts of IRS audits on reporting compliance among the general taxpayer population. We do not address impacts on other types of tax compliance (such as filing and payment compliance) or the effect of IRS enforcement actions other than audits (such as automated programs, collection activities, penalties/interest and criminal investigations).
[4] It is important to note that audit coverage rate is an imperfect measure of audit activity since the mix of audits (i.e., correspondence or in-person) has changed over time.
[5] TPI is the sum of all positive amounts of income and excludes income losses, such as from investments.
[6] See the lists of return categories, their definitions, and their relative importance as percentage of the taxpayer population in Table 8 of the Appendix.

Figure 1. Audit Rates by Return Category (Relative to 2008)



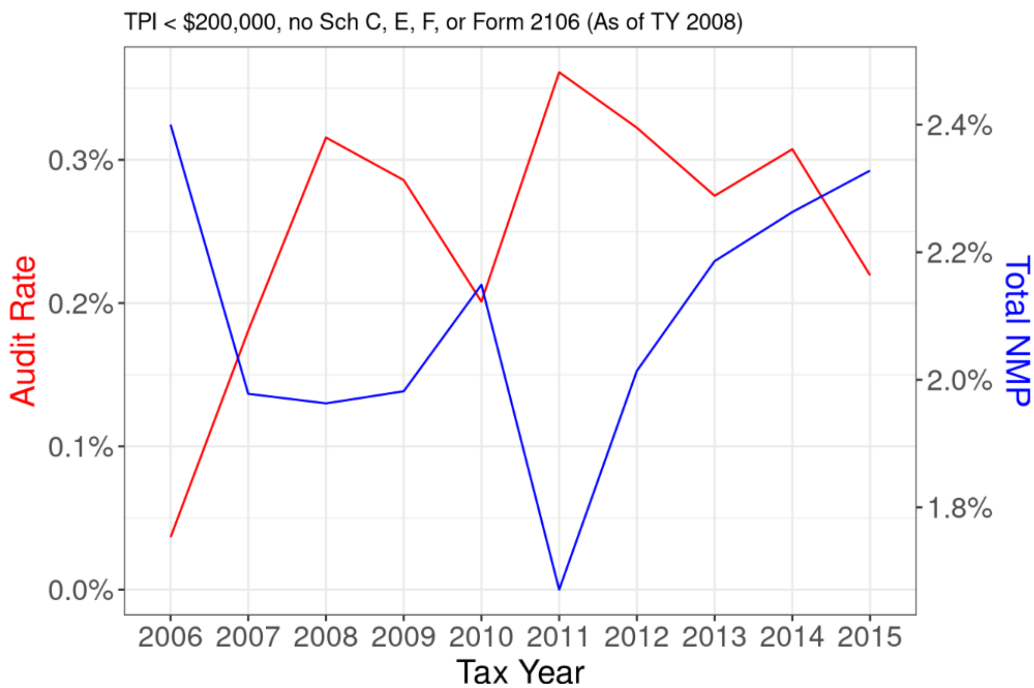
Descriptive evidence suggests the existence of co-movement between audit rates and noncompliance—measured by the Net Misreporting Percentage (NMP) on tax.[7] As an example, Figure 2 illustrates the audit coverage and misreporting rates on tax after refundable credits (i.e., bottom line total tax) for individuals in return category 272 – a group that comprises over half of all individual tax returns (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[8] and do not claim the EITC). The audit rate is lagged by three years to reflect an assumed delay in taxpayers'

[7] 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).

[8] 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.

knowledge, experience, or impressions of IRS audit levels. Figure 2 shows how noncompliance tends to move in the opposite direction of the lagged audit rate, suggesting the presence of a general indirect effect among this large group of taxpayers.[9]

Figure 2. Audit Coverage and NMP Trends, TYs 2006-2015 for Taxpayers with TPI <$200k and no EITC, Schedule C, E, F or Form 2106 (55.3% of the Population)



Note: Audit rate (in red) is lagged by three years to reflect delays in taxpayer knowledge of IRS audit levels.

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 based on the extent of third-party reporting. Taxpayers are more likely to respond to changing audit rates if the IRS is able to detect and confirm noncompliance. A related but separate issue is the set of line items that audits are targeting: line items subject to automated matching programs

[9] The figure captures only the NRP-detected amount of noncompliance and does not include adjustments made for noncompliance undetected in the examination process. As such, aggregate noncompliance in this paper is distinct from that of IRS tax gap estimates, which employ Detection Controlled Estimation to account for differences in examiner ability.

(which are not audits) may be less affected by changing audit rates than line items that are the typical subjects of audits.

This paper adds to the literature on the indirect effect of audits by using alternative model specifications and by exploiting new individual microdata to capture noncompliance. We differ from prior research (Dubin, Graetz and Wilde, 1990; Tauchen, Witte, and Beron, 1993; Dubin, 2007; and Plumley, 1996) in a number of ways. First, our econometric specification relies not on the contemporaneous audit rate, but rather on a lagged measure of the audit rate. Taxpayers do not have contemporaneous knowledge of the audit rate since this information disseminates with a lag, through both official and private information channels. In addition to better capturing the timing of taxpayer behavior, this lag has the benefit of reducing concerns about the endogeneity of the audit rate, since it is not plausible to argue that current noncompliance behaviors drive prior-year audit rates. Further, most prior papers estimate the impact of audit rates on aggregate measures of compliance; our use of microdata allows for the inclusion of taxpayer-level controls and, importantly, the specification of audit rates that are most relevant to each taxpayer's tax situation. We also differ from prior work by 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 audit 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 \$5 to \$20 of indirect revenue (roughly 1 to 6 times the direct revenue). Our findings are within the range of magnitudes 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 income received and taxes owed 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 compliance. They find that taxpayers who share tax preparers with IRS-visited/audited taxpayers tend to be more compliant with tax obligations.[10] 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 then 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 audits spread through the network by word of mouth. As shown by Chetty *et al.* (2013) when documenting the

[10] 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.

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. In lieu of geographic proximity, Collins *et al.* (2025) proxy knowledge of IRS enforcement through social network data capturing zip code-to-zip code connectedness. They find that compliance responses to tax enforcement actions are stronger in areas that are more socially connected.

Media coverage of specific audits and audit rates can also 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)[11] to find that local audit rates stimulate individual compliance.[12] They estimate that the indirect effect of audits is twice the size of the direct effect. The source of variation in audit rates relates to differences in resources available to IRS district offices that conducted the audits. 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

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

[12] 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.

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 many 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).

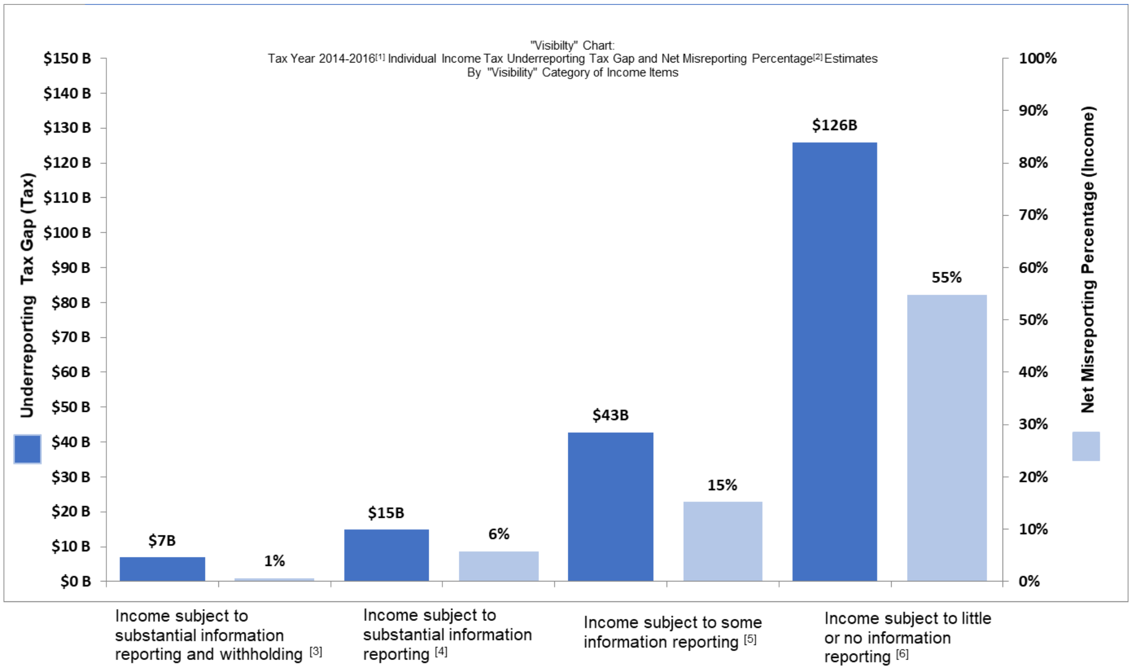
We interpret the behavior of the individuals in the NRP sample as being representative of similar taxpayers in the general population. However, we are interested in the aggregate audit rate faced by the segment of the population represented by the NRP taxpayer—not the audit probability of the taxpayer 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 2006-2015. For each return, we compare 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 categories, NMA is calculated as *Corrected Amount – Reported Amount*, and positive NMA values indicate understatements of taxable income. 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 indicate overstatements of offsets.

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 (see Figure 3). Accordingly, 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.

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



Source: Internal Revenue Service (2022)

Table 2 summarizes line items by visibility group. Visibility Group 1 is the income category subject to the most information reporting and withholding while Visibility Groups 4-6 are 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 *a priori* whether, in response to changes in the audit rate, taxpayers might be expected to change their compliance behavior on high visibility line items. Many of these are validated by automated document matching programs, not audits. It is also unclear whether taxpayers might be expected to change compliance on items with *no* information reporting, since such income can be difficult to validate through audits. In our analysis, we evaluate NMA for each Visibility Group separately.

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 fully compliant behavior and not to the irrelevance of line items for the given taxpayer. We also trim taxpayers with negative NMA, since we focus on noncompliance in the form of underreporting income or overstating offsets.

Table 2. Visibility Group Definitions

Visibility Group	Category	Line Items Included	Visibility
1	Income	Wages & Salaries	**High:** subject to substantial information reporting and withholding (W2)
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 (1099-R, 1099-G, 1099-DIV, 1099-INT, SSA-1099)
3	Income	Partnerships/S corp. income, capital gains, and alimony income	**Limited:** subject to some information reporting (1099-MISC, 1099-DIV)
4	Income	Nonfarm proprietor income, other income, rents and royalties, farm income, and form 4797 income	**Low:** subject to little or no information reporting (1099-MISC)
5	Offsets to income	Adjustments, deductions, and exemptions	**Low:** subject to little or no information reporting
6	Offsets to tax	Refundable and nonrefundable credits	**Low:** subject to little or no information reporting

3.2 Independent Variables

3.2.1 Audit Rates

Using IRS enforcement data, we construct the audit rate for a given tax year 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.[13] We also create separate audit rates for each return category (see Table 9 of the Appendix for a listing of these categories). As the third column of Table 9

[13] We calculate tax rates on a tax year basis rather than a calendar or fiscal year basis. Future research can explore the sensitivity of our results to alternate specifications of tax rates.

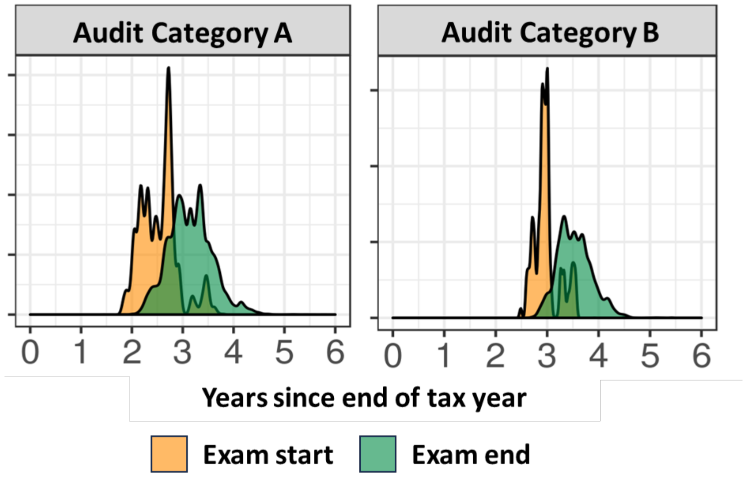
shows, about two-thirds of taxpayers fall in the category of having annual income below $200,000 and no active business income or expenses (return categories 272 and 273).

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 – the audit rate – is specified at the return category level. Each observation in our NRP sample is assigned the audit rate for that return's – reflecting the assumption 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 three-year lag of audit rate in the regressions. The choice to lag the audit rate arises from the natural delay in audit 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 should be notified in late 2013 (at the latest). In spring 2014, the taxpayer will file the TY2013 return. Thus, any information that taxpayers may glean about the audit experiences of people in their social or professional networks is likely to reflect this three-year lag in relation to current compliance behaviors.[14] We also specify a two-year lag in robustness checks and find slightly smaller estimates of the indirect effect.

[14] Taxpayers may also glean information about IRS audit levels from the IRS Data Book (www.irs.gov/statistics/soi-tax-stats-irs-data-book), published by the IRS Statistics of Income Division. The Data Book releases information about overall enforcement levels (total audits conducted and total recommended additional tax) with a lag of two years. More granular information (such as audit coverage rates by return category) are released with a lag of five years. We conduct sensitivity analysis using a two-year lag and find qualitatively similar results.

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 a 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.

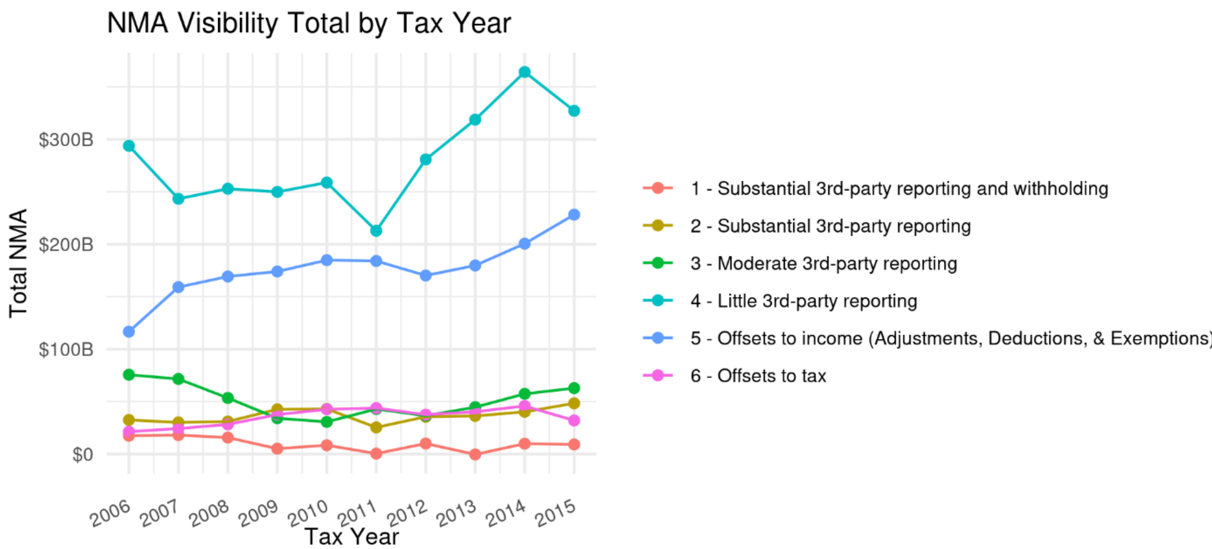
3.3 Data Summary

Figure 5 summarizes sample size by return category. Except for return category 271, our sample includes at least 5,000 returns for each return category during TYs 2006-2015.

Figure 5: Counts of NRP Returns by Return Category (TYs 2006-2015)

Figure 6 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 key takeaway from Figure 6 is that not only does noncompliance vary across groups of line items based on their visibility (consistent with Figure 3), it also varies over time within a visibility group. This can be driven by changes in total tax liability (e.g., due to economic growth) or due to changes in compliance behavior. We control for true tax liability in our analysis to assess the impact of audit rates on compliance behavior.

Figure 6: Aggregate NMA* over Time, by Visibility Group (Weighted)



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

Compliance also varies by the type of taxpayer. Figure 7 disaggregates NMA totals by return category. 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, return category 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). Return categories 279-281, despite comprising only 3.7 percent of the population (per Table 9), contribute almost 25 percent of misreporting on Visibility Group 3 income. Return category 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. In our analysis, we assess the impact of audit rates specific to each return category to account for these differences in compliance.

Figure 7: Aggregate NMA by Return Category (Weighted)

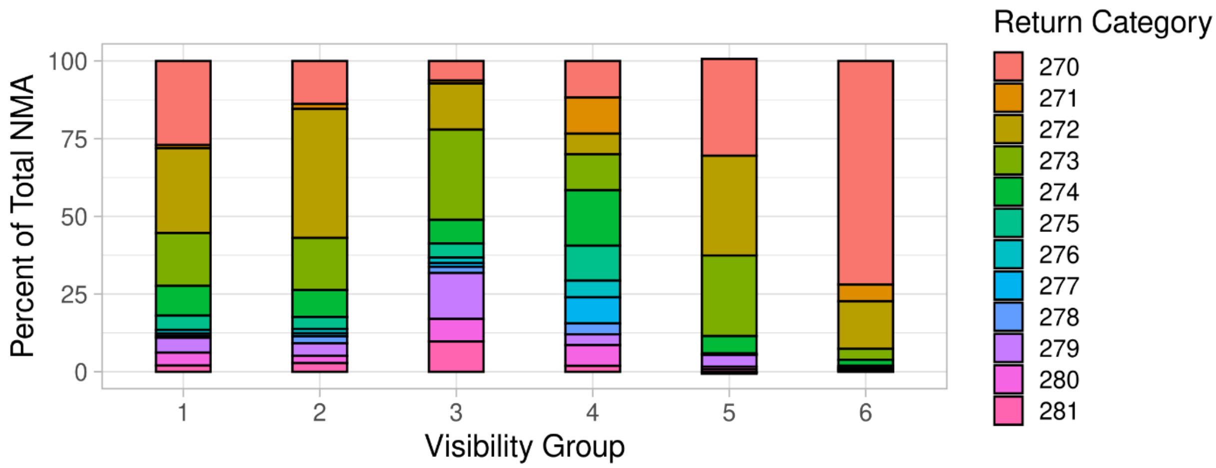


Table 3 summarizes the dependent and independent variables in our model by tax year. Observations are weighted by NRP sampling weights. Dollar-denominated variables (NMAs and Correct Amounts) are adjusted to 2018 dollars. Trends in NMAs and Correct Amounts vary across visibility groups. Commensurate 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	2015
Dependent Variable (NMA)										
Visibility Group 1	$163	$159	$133	$44	$70	$3	$78	-$3	$73	$66
Visibility Group 2	$303	$265	$263	$370	$359	$202	$276	$276	$297	$353
Visibility Group 3	$705	$630	$453	$296	$256	$341	$283	$340	$424	$459
Visibility Group 4	$2,743	$2,144	$2,145	$2,171	$2,162	$1,694	$2,182	$2,426	$2,694	$2,392
Visibility Group 5	$876	$1,157	$1,231	$1,286	$1,343	$1,315	$1,214	$1,270	$1,403	$1,575
Visibility Group 6	$199	$214	$239	$326	$356	$349	$291	$306	$339	$234
Independent Variables										
Audit Rate										
	0.86%	0.74%	0.90%	0.92%	0.86%	0.75%	0.69%	0.57%	0.52%	0.54%
Correct Amount										
Visibility Group 1	$50,206	$50,104	$48,942	$48,487	$47,585	$45,856	$47,531	$47,154	$48,838	$50,878
Visibility Group 2	$9,522	$10,334	$9,408	$9,035	$10,198	$9,531	$9,572	$9,468	$9,429	$9,938
Visibility Group 3	$10,534	$10,600	$8,454	$4,701	$6,288	$6,088	$8,352	$7,945	$10,902	$10,843
Visibility Group 4	$5,553	$4,701	$4,638	$4,541	$4,841	$3,920	$4,611	$4,311	$5,347	$4,902
Visibility Group 5	$20,748	$21,369	$22,010	$22,178	$22,183	$21,750	$22,478	$22,444	$22,933	$23,239
Visibility Group 6	$848	$980	$998	$1,088	$1,002	$918	$901	$890	$920	$958
Filing Status										
Single/other	60%	62%	62%	62%	61%	63%	62%	63%	63%	63%
Married filing jointly	40%	38%	38%	38%	39%	37%	38%	37%	37%	37%
Total Exemptions										
0 or NA	7%	7%	7%	6%	5%	6%	7%	7%	7%	6%
1	37%	37%	38%	39%	39%	40%	39%	39%	40%	41%
2	27%	28%	26%	27%	28%	27%	27%	28%	25%	28%
3	13%	13%	14%	12%	13%	12%	12%	12%	13%	11%
4	10%	9%	10%	10%	10%	9%	10%	10%	10%	9%
5+	5%	6%	6%	6%	5%	5%	5%	5%	6%	5%
Had wage income	85%	85%	85%	84%	83%	83%	83%	83%	82%	84%
Claimed child tax credit	19%	19%	18%	17%	17%	15%	15%	16%	15%	15%
Itemized	36%	36%	34%	33%	34%	33%	32%	31%	30%	30%
Deducted mortgage interest	29%	29%	27%	27%	27%	25%	24%	24%	22%	22%
Over 65	13%	13%	14%	14%	14%	15%	15%	16%	15%	17%
Used paid preparer	61%	61%	60%	58%	59%	58%	59%	59%	56%	55%
Filed electronically	48%	62%	68%	72%	79%	83%	83%	71%	71%	72%

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 audits and other drivers of compliance:[15]

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

We run a separate regression for each visibility group. Return-level NMA on those line items is our dependent variable. Since there are positive and negative outliers of NMA, we winsorize NMAs at the 1st and 99th percentiles. The audit rate is the primary explanatory variable of interest. As discussed previously, each taxpayer is assigned the audit rate for their return category (*g*) for the tax year in question. We lag the audit rate by three years to reflect the delay in audit processing time.[16] We hypothesize that β_1 will be negative—a decrease in audit rates should lead to an increase in noncompliance. As we exploit the within-return category variation in audit rates across years, it is important to stress that even though overall audit rates are lower at the end of our period of analyses than at its beginning, there were numerous positive year-to-year changes. Thus, we identify our parameters of interest relying both on negative and positive shifts of audit rates. This imposes a very mild assumption of symmetry on our econometric specification that informs our interpretation of β_1 – it tells us the expected dollar amount by which NMA rises or falls in response to a one percentage point change in the audit rate, in either direction.[17]

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

[16] For robustness, we also estimate the impact of a two-year lag of audit rates.

[17] For robustness, we estimate separate effects of the audit rate by time period, splitting our sample in 2008 (corresponding to audit rate inflection point shown in Figure 1).

We control for the correct amount that should have been reported on the line items in question, for each visibility group. The true tax liability has a large influence on the magnitude of potential noncompliance. True tax reflects factors such as an individual's tax situation and changes to tax policy; by controlling for these factors, we ensure that the remaining variation in NMA arises from behavioral responses to audit rates rather than from structural reasons. Additional taxpayer control variables refer to the variables described in Section 3.2.2. We include fixed effects for return category. These capture time-invariant determinants of compliance that are unique to each return category, 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.[18] 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, for the reasons given above. 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 do not 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

[18] 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 return category-tax year fixed effects. Such effects would be collinear with our audit rate variables, which do not vary within a return category and tax year. In future work, we hope to include variables capturing known policy changes for certain return categories.

allocation (but not in response to improved compliance), thereby creating a natural experiment for evaluating the causal effect of audit rates.

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 audits during this time period.

5.1 Regression Results

Table 4 presents the primary regression results.[19] Full results are shown in Table 10 of the Appendix. Audit rates in Table 4 have the expected negative effect on noncompliance for Visibility Groups 1, 3 and 4. These effects are also statistically significant. For Visibility Group 1 (wages and salaries), a one percentage point increase in audit rates decreases noncompliance on a return by $36. Wages and salaries are subject to a large degree of information reporting and withholding, and noncompliance is relatively rare. Thus, it is intuitive that the indirect effect is small.

The effects on Visibility Groups 3 and 4 are larger: a one percentage point increase in the audit rate lowers noncompliance by $446 and $390, respectively. Visibility Group 3 includes sources of income that are often the target of audits (such as partnership/S corporation income, capital gains, and alimony income), suggesting that noncompliance on these line items should

[19] Since taxpayers can appear in more than one Visibility Group regression, there is some degree of correlation in the errors among the six regressions in Table 4. However, this does not affect our primary findings on the impact of the audit rate on compliance.

respond more to audit rate fluctuations. The largest portion of noncompliance arises from Visibility Group 4 (see Table 3), which in turn leaves more room for a compliance response to changes in audit rates.

In Table 4, audit rates also have positive effects on noncompliance for some visibility groups. There is a slightly positive but statistically insignificant effect of audit rates on Visibility Group 2 noncompliance. The positive effects on Visibility Groups 5 and 6 are statistically and economically significant. A one percentage point increase in the audit rate increases noncompliance on offsets to both income and tax by $95. We hypothesize that this unexpected positive effect arises from noncompliance shifting – as audit rates rise, taxpayers improve compliance on some line items but may shift noncompliance to other line items. Evidence of noncompliance shifting has been observed in some enforcement contexts, based on our conversations with IRS officials. Compliance shifting may occur on both the extensive and intensive margins: we find the average combined effect is $95 of increased noncompliance per percentage point increase in the audit rate.

Table 4: Main Regression Results (Full Sample, 3 Year Lag)

	Dependent Variable: NMA					
	Visibility Group 1	**Visibility Group 2**	**Visibility Group 3**	**Visibility Group 4**	**Visibility Group 5**	**Visibility Group 6**
Audit Rate (3 Year Lag)	-36.408***	11.456	-446.515***	-391.586***	94.575***	94.597***
	(6.079)	(14.816)	(108.521)	(110.957)	(22.162)	(7.948)
Constant	3,001.906***	428.225***	3,494.841***	3,624.539***	-619.457***	385.595***
	(44.112)	(48.696)	(379.251)	(601.24)	(69.681)	(67.866)
Observations	109,639	103,737	57,884	84,507	140,257	83,114
Adjusted R^2	0.045	0.013	0.01	0.084	0.169	0.212
F Statistic	201.104***	53.505***	23.390***	300.698***	1,100.519***	862.656***

Controls include a dummy variable for taxpayers older than 65, a dummy variable indicating married filing jointly, dummy variables each indicating whether the taxpayer claims 1, 2, 3, 4, or 5 or more total exemptions, a dummy variable indicating whether they claimed the Child Tax Credit, a dummy variable indicating whether the taxpayer filed electronically, a dummy variable identifying taxpayers who deducted mortgage interests, a dummy variable indicating the use of a paid tax preparer, a dummy variable indicating the returns that use itemized deductions, wage income, and the correct amount the return should have reported. Regressions include return category fixed-effects. Standard errors in parentheses.

Statistical significance: *** 1% ** 5% * 10%

We conduct two robustness checks in our estimation of Equation (1). First, we specify a two-year lag of the audit rate instead of a three-year lag to align with the earliest audit start rates observed in Figure 4. These results are presented in Table 11 of the Appendix and are largely similar to our main results, with two exceptions: the impact of audit rates on Visibility Group 4 and 5 become statistically insignificant under a two-year lag. We translate the implications of these changes on the overall return on investment of IRS audits in Section 5.3.

Our second robustness check assesses heterogenous effects over time. Our NRP sample period of 2006-2015 is long enough that tax compliance behavior plausibly could have shifted due to changes in how taxpayers receive information about audit levels and due to the inflection point in audit coverage observed in 2008 (per Figure 1). For robustness, we estimate whether the comprehensive indirect effect has changed over time. We split the sample into two time periods (2006-2010 and 2011-2015)[20] and estimate Equation (1) separately for each period. Table 5 presents these results. As in the full sample, audit rates have the expected negative effect on noncompliance for Visibility Groups 1, 3 and 4. The effect is much larger in the late period for Visibility Group 4 than in the early period. There are also qualitative differences between the two periods. Audit rates have a negative effect for Visibility Groups 2 and 5 in the late period – a departure from the full sample and early period. The positive effect for Visibility Group 6 also becomes statistically insignificant in the late period. These findings suggest that noncompliance shifting has subsided in more recent years. Since the late period results are likely to be more

[20] The sample split is intended to align with the inflection point in the audit coverage trend in 2008, since 2008 audit rates align with 2011 compliance per our 3-year lag of the audit rate. Further, in the late period, there were larger declines in non-audit enforcement actions that may have impacted compliance behavior.

relevant today, we use them as a robustness check in the translation of the comprehensive indirect effect into revenue impact.

Table 5: Regression Results by Time Period

	Dependent Variable: NMA					
	Visibility Group 1	Visibility Group 2	Visibility Group 3	Visibility Group 4	Visibility Group 5	Visibility Group 6
2006-2010						
Audit Rate (3 Year Lag)	-37.632***	20.476	-490.632***	-268.468**	97.739***	89.434***
	(7.616)	(16.924)	(153.614)	(133.104)	(27.186)	(8.91)
Constant	3,193.104***	439.141***	4,041.469***	2,985.730***	-702.462***	350.185***
	(61.219)	(56.818)	(552.690)	(882.253)	(88.692)	(79.122)
Observations	54,585	51,487	26,425	38,747	68,475	43,087
Adjusted R^2	0.051	0.014	0.014	0.09	0.161	0.209
F Statistic	114.430***	28.592***	15.046***	147.993***	506.145***	439.706***
2011-2015						
Audit Rate (3 Year Lag)	-56.049**	-116.394**	-190.149	-1,519.931***	-446.550***	10.81
	(25.758)	(49.345)	(229.284)	(369.481)	(87.198)	(44.273)
Constant	2,891.528***	672.034***	2,404.402***	6,390.653***	596.715***	641.668***
	(82.963)	(123.865)	(648.772)	(1,075.520)	(200.749)	(145.363)
Observations	55,054	52,250	31,459	45,760	71,782	40,027
Adjusted R^2	0.038	0.012	0.008	0.084	0.18	0.22
F Statistic	84.535***	26.305***	10.686***	162.371***	604.808***	433.896***

Controls include a dummy variable for taxpayers older than 65, a dummy variable indicating married filing jointly, dummy variables each indicating whether the taxpayer claims 1, 2, 3, 4, or 5 or more total exemptions, a dummy variable indicating whether they claimed the Child Tax Credit, a dummy variable indicating whether the taxpayer filed electronically, a dummy variable identifying taxpayers who deducted mortgage interests, a dummy variable indicating the use of a paid tax preparer, a dummy variable indicating the returns that use itemized deductions, wage income, and the correct amount the return should have reported. Regressions include return category fixed-effects. Standard errors in parentheses.
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 and Table 5 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 6 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 three 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 6 – 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 three 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 6. 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 audit 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.[21] It is important to note

[21] 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.

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-return category observations where this is the case.

Table 7 presents our estimates of the general indirect ROI, along with sensitivity analysis on the audit rate coefficients used. Under a three-year lag of the audit rate, we find that a dollar of audit cost generates $4.90-6.60 in indirect revenue (depending on whether we use all point estimates, all statistically significant coefficients or all negative coefficients from Table 4). The steep decline in audit coverage after 2008 is associated with larger impacts. A dollar of audit cost generates $4.00 in indirect revenue before the 2008 inflection point but almost $20 thereafter. These results suggest that steep cuts to IRS budgets will have disproportionally more serious consequences on voluntary compliance than more modest cuts. For robustness, we also evaluate the indirect ROI under a two-year lag of the audit rate. In this scenario, a dollar of audit cost generates $3.0 in indirect revenue – the lowest ROI in our evaluated scenarios.

Table 7: General Indirect Return on Investment with Sensitivity Analysis

	Audit Rate Coefficient Used						**Indirect ROI by Years**		
	Vis 1	**Vis 2**	**Vis 3**	**Vis 4**	**Vis 5**	**Vis 6**	**06-15**	**06-10**	**11-15**
3 Year Lag									
All Coefficients	-36.41	11.46	-446.52	-391.59	94.58	94.60	**4.9**		
All Sig. Coeff.	-36.41	0.00	-446.52	-391.59	94.58	94.60	**5.0**		
All Neg. Coeff.	-36.41	0.00	-446.52	-391.59	0.00	0.00	**6.6**		
Early Period	-37.63	20.48	-490.63	-268.47	97.74	89.4	**4.4**	**4.0**	
Late Period	-56.05	-116.39	-190.15	-1519.93	-446.55	10.81	**20.0**		**21.4**
2 Year Lag									
All Coefficients	-38.92	-28.75	-298.47	34.62	7.55	87.20	**3.2**		

Table 8 summarizes the direct ROI, general indirect ROI, and combined ROI for four groupings of taxpayers based on TPI.[22] 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 audit cost during this 2006-2015 time period generated $3.40 of direct revenue on average and almost $9 when applied to audits of taxpayers earning $400k and above.

We calculate a range of general indirect ROIs based on the full sample, three-year lag results from Table 7: a low end using all coefficients and a high end using the late period coefficients. $1 of audit cost generates around $5-$20 of general indirect revenue, with larger impacts on taxpayers earning between $200k-$400k. The general indirect ROI increases monotonically with income except for the highest income group. This result could derive from difficulty in measuring noncompliance at the high end of income or from behavioral differences – high income taxpayers may be less responsive to audit rates due to their ability to hire sophisticated tax advisors, for example.

Finally, combined ROI in Table 8 shows the total impact of a dollar of audit cost. $1 of audit costs generates, on average, roughly $8-23 of total revenue when considering direct and indirect effects. This translates to roughly 1 to 6 times the direct revenue effect. 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 audit costs, it led to an estimated loss of at least $1.8B in direct and indirect tax revenue and potentially up to $5B.

[22] 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 audit 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 audit allocations to the various categories.

Table 8. Full Return on Investment by Income Group

Return Total Positive Income	Direct ROI	General Indirect ROI	Combined ROI
< $100K	2.1	3.3 - 13.2	5.4 - 15.3
$100K to under $200K	2.9	4.1 - 23.8	7.0 - 26.7
$200K to under $400K	3.1	10.3 - 45.5	13.4 - 48.6
$400K and over	8.9	7.3 - 23.0	16.2 - 31.9
All Groups	**3.4**	**4.9 - 20.0**	**8.3 - 23.4**

6 Discussion

While most research on the impact of IRS audits on overall tax compliance evaluates specific local networks, this paper contributes to a small literature on the "comprehensive" general indirect effects of IRS audits. 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 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 audit 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 arguably 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 could arguably be less sensitive to audit rates per se (e.g., since they may result from errors rather than conscious compliance decisions). 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. We also find evidence of noncompliance shifting toward offsets, a behavior that has been observed in some IRS enforcement contexts.

Our top-level finding is that IRS audits of individual income tax returns had a combined ROI of 8:1 to 23:1 during the 2006 to 2015 Tax Years. Put another way, the general indirect effect was 1 to 6 times 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. Estimated ROIs are larger in later years when audit rates (and other enforcement actions) declined precipitously. These results suggest that steep cuts to IRS budgets will have disproportionally more serious consequences on voluntary compliance than more modest cuts.

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 (such as taxpayer burden); and the tax law in place in a given year (as well as state tax complexity). Our estimates are not a universal constant, as is suggested by the larger effects we find for the late period in our sample. More generally, we have not explored various forms of heterogenous effects in the comprehensive indirect effect, such as differences in taxpayers who use preparers versus those who do not, taxpayers in different tax situations, or the aforementioned temporal heterogeneity.

Our estimates of the general indirect effect are not directly comparable to estimates of the specific indirect effect, such as those provided in Boning et al. (2024). These two types of indirect effect differ in terms of information channels, persistence and heterogeneous impact across the population. Both contribute to the indirect impact of IRS activity. Future work can explore a unified econometric framework for simultaneously estimating both the general and specific indirect effects.

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 return category. 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 enforcement programs at large, 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

Table 9. IRS Return Category Definitions

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

*TPI stands for Total Positive Income. TGR refers to Total Gross Revenues from self-employment including farm proprietorships.

Table 10. Full 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 (Lag 3)	**-36.408*****	**11.456**	**-446.515*****	**-391.586*****	**94.575*****	**94.597*****
	(6.079)	**(14.816)**	**(108.521)**	**(110.957)**	**(22.162)**	**(7.948)**
Corrected TARC	0.00004**	0.001***	0.0003***	0.001***	-0.003***	-0.001***
	(0.00002)	(0.0001)	(0.00004)	(0.0001)	(0.0002)	(0.0001)
Total Exemptions 1	4.759	131.239***	1,074.637***	3,595.410***	206.621***	8.523
	(10.677)	(33.078)	(233.941)	(530.315)	(42.073)	(64.677)
Total Exemptions 2	-58.083***	329.294***	1,482.147***	3,519.072***	3,347.234***	975.527***
	(13.014)	(38.316)	(297.698)	(562.723)	(51.142)	(65.401)
Total Exemptions 3	-67.508***	375.386***	1,901.969***	4,067.008***	4,496.495***	1,545.603***
	(14.637)	(42.269)	(327.143)	(584.249)	(57.536)	(66.033)
Total Exemptions 4	-67.993***	296.853***	1,976.338***	4,399.945***	4,953.995***	1,652.808***
	(16.291)	(45.697)	(348.314)	(607.300)	(64.272)	(66.852)
Total Exemptions 5+	-52.464***	389.551***	3,120.493***	5,188.102***	6,063.777***	1,778.572***
	(17.964)	(49.474)	(376.143)	(632.934)	(71.115)	(67.695)

Wage Income	-2,785.597***	7.237	-1,028.289***	-1,263.023***	417.115***	-106.223***
	(41.078)	(18.055)	(119.925)	(169.316)	(32.377)	(17.111)
Claimed child tax credit	12.93	-150.227***	-826.717***	-1,747.315***	-1,209.072***	-469.688***
	(8.074)	(20.535)	(170.611)	(212.378)	(32.463)	(12.063)
Itemized	-53.494***	-4.897	-624.027***	912.249***	2,541.315***	7.007
	(11.669)	(21.035)	(136.172)	(238.846)	(39.919)	(20.938)
Deducted mortgage interest	4.446	-30.053	589.571***	36.045	-1,280.056***	-181.770***
	(11.798)	(21.577)	(137.678)	(242.642)	(41.693)	(21.245)
Over 65	-87.150***	295.398***	-946.440***	-2,187.147***	-7.936	-19.059
	(11.013)	(18.406)	(128.507)	(203.837)	(34.781)	(20.493)
Used paid preparer	37.098***	-68.429***	582.413***	474.936***	-90.274***	45.171***
	(5.330)	(12.619)	(101.463)	(145.787)	(20.590)	(9.807)
Filed electronically	15.429***	-30.955**	-510.057***	-1,413.229***	-75.407***	28.118***
	(5.838)	(13.044)	(94.946)	(142.289)	(21.876)	(10.686)
Filing Status	50.557***	-79.069***	-386.582*	28.71	-3,383.204***	-1,053.292***
	(8.738)	(22.214)	(205.157)	(225.324)	(33.918)	(13.629)
Constant	3,001.906***	428.225***	3,494.841***	3,624.539***	-619.457***	385.595***
	(44.112)	(48.696)	(379.251)	(601.240)	(69.681)	(67.866)
Observations	109,639	103,737	57,884	84,507	140,257	83,114
Tax Year Fixed effect	N	N	N	N	N	N
Adjusted R^2	0.045	0.013	0.01	0.084	0.169	0.212
F Statistic	201.104***	53.505***	23.390***	300.698***	1,100.519***	862.656***
Degrees of Freedom	109,541	103,685	57,841	84,427	140,133	83,002

Regressions include return category fixed-effects. Standard errors in parentheses.
Statistical significance: *** 1% ** 5% * 10%

Table 11: Sensitivity Analysis (2 Year Lag)

	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)	-38.922***	-28.749	-298.465**	34.616	7.553	87.200***
	7.572	17.621	118.404	130.568	27.037	9.914
Constant	3,011.292***	497.187***	3,322.375***	2,927.569***	-480.447***	384.007***
	45.015	52.852	397.141	619.594	76.642	68.945
Observations	109,639	103,737	57,884	84,507	140,257	83,114
Adjusted R^2	0.045	0.013	0.01	0.084	0.169	0.212
F Statistic	200.724***	53.586***	22.979***	300.178***	1,099.679***	859.520***

Controls include a dummy variable for taxpayers older than 65, a dummy variable indicating married filing jointly, dummy variables each indicating whether the taxpayer claims 1, 2, 3, 4, or 5 or more total exemptions, a dummy variable indicating whether they claimed the Child Tax Credit, a dummy variable indicating whether the taxpayer filed electronically, a dummy variable identifying taxpayers who deducted mortgage interests, a dummy variable indicating the use of a paid tax preparer, a dummy variable indicating the returns that use itemized deductions, wage income, and the correct amount the return should have reported. Regressions include return category fixed-effects. Standard errors in parentheses.
Statistical significance: *** 1% ** 5% * 10%