SEEKING PROFESSIONAL HELP: HOW PAID PREPARERS DECREASE TAX COMPLIANCE

Jason DeBacker, Bradley T. Heim, Anh Tran,
and Alexander Yuskavage

Legal services, such as tax preparation, claim to help clients better comply with the law while maximizing their benefits. We test this claim using data from about 135,000 random audits conducted by the US Internal Revenue Service between 2006 and 2014. Supplementing this nationally representative cross section of data on tax compliance with an instrumental-variable approach, we find that tax preparers actually reduce compliance, increasing taxpayers' underreporting of income by roughly $3,900 per tax return. However, we find that volunteer tax preparers assisting low-income taxpayers have compliance rates similar to self-prepared returns, suggesting that differences in clientele or pecuniary incentives can affect the relationship between tax-preparation services and tax compliance.

Keywords: tax compliance, tax audit, tax evasion, tax avoidance, tax preparers

JEL Codes: H24, H26

I. INTRODUCTION

Paid tax preparation is a legal service that has vast economic importance and is frequently employed by Americans. Annually, about 60 percent of US tax filers use paid preparers, professionals with expertise in understanding the Internal Revenue Code. These tax preparers face two potentially opposing pressures: helping clients correctly report their taxes and minimizing the taxes their clients owe. With

Jason DeBacker: Darla Moore School of Business, University of South Carolina, Columbia, SC, USA (jason.debacker@moore.sc.edu.com); Bradley T. Heim: O'Neill School of Public and Environmental Affairs, Indiana University, Bloomington, IN, USA (heimb@indiana.edu); Anh Tran: O'Neill School of Public and Environmental Affairs, Indiana University, Bloomington, IN, USA (trananh@indiana.edu); Alexander Yuskavage: Office of Tax Analysis, US Department of the Treasury, Washington, DC, USA (alexander.yuskavage@treasury.gov)

Electronically published May 21, 2024

National Tax Journal, volume 77, number 2, June 2024.
 https://doi.org/10.1086/728928

uncertain legal boundaries, tax minimization may encourage behavior that tax-enforcement agencies find to be incongruent with the revenue code. How much such incentives drive professional preparers toward tax noncompliance is an empirical question. Our study presents new evidence addressing three related questions regarding the role of professional tax preparers in tax compliance.

First, do tax preparers improve tax compliance? We find that preparers significantly increase taxpayers' income underreporting, which we measure by adjustments to income following an Internal Revenue Service (IRS) audit. Returns prepared by paid professionals are found to understate taxable income by $3,900 after controlling for taxpayer characteristics, mean local income and audit rates, the complexity of the return, and time and zip code fixed effects. To put this in perspective, this represents about an 87 percent increase in the average amount of underpaid taxes, an estimated $518 loss in tax revenue per professionally prepared tax return each year.

Second, what techniques do tax preparers use to help taxpayers minimize their taxes in a potentially noncompliant manner? We decompose the line items that are adjusted on filers' tax returns and find that just a few income and deduction items account for most of the differences in audit adjustments between self-prepared and professionally prepared returns.[1] In particular, underreporting of Schedule C income (income from sole proprietorships) and overclaiming of the Earned Income Tax Credit (EITC) account for almost the entire difference in total audit adjustments. These techniques exploit the income sources and deduction items with little third-party verification available to the IRS.

Finally, is this noncompliance driven by demand (taxpayers) or supply (preparers)? The patterns identified in our analysis indicate that characteristics of both parties may be important. On the demand side, we find that when using a paid preparer, men evade much more aggressively than women, and high-income taxpayers evade more than low-income taxpayers. On the supply side, we find certified public accountants (CPAs) to be among the most conservative and enrolled agents and preparers working for small firms to be among the most aggressive. We do not find increases in noncompliance among returns prepared by Volunteer Income Tax Assistance (VITA), where the preparers lack any financial benefit from aggressive preparation. To explore the cause behind these different behaviors among tax preparers, we consider whether there are differential effects of preparers based on the type of preparer and on how competitive the local tax-preparation service market is. We find suggestive evidence for the former but weaker evidence for the latter.

Our research design attempts to overcome two significant issues in estimating the role paid preparers play in tax compliance: selection into audit and the endogenous choice of tax-return preparation method. To address endogenous audit selection,

[1] Our definition of self-preparation includes taxpayers who use software to assist in their tax preparation. Note that about 30 percent of taxpayers use software to prepare their return and only about 6 percent of taxpayers self-prepare without the assistance of software.

we use data from the randomized audits conducted by the IRS National Research Program (NRP). To address the taxpayer's endogenous decision to use tax-preparation services, we use instrumental-variable (IV) models for our baseline estimates. We believe this approach adds value to a literature that previously relied on ordinary least squares (OLS) and structural modeling, but we provide OLS results for comparison and offer a discussion of the potential bias in the case that the identifying assumptions behind our instruments were invalid.

The early literature focusing on the effect of tax preparers on compliance offers somewhat mixed results. Klepper and Nagin (1989) and Klepper, Mazur, and Nagin (1991) both use data from the 1982 Tax Compliance Measurement Program (TCMP) and find that tax preparers reduce noncompliance by helping filers to more consistently report items that have clear reporting requirements. However, Klepper and Nagin (1989) find that preparers tend to increase noncompliance on lines of the return for which there is more ambiguity, as measured by the variance in revenue rulings. Erard (1993) uses data from the 1979 TCMP to find that paid preparers who are CPAs or lawyers increase noncompliance rates by about 4.5 times what would be found on self-prepared returns. He finds smaller effects, an increase in noncompliance of about 15 percent, for other types of preparers. Erard (1997) uses the 1982 TMCP data with a different empirical strategy and finds similar effects of preparers on compliance. Hite and Hasseldine (2003) use a sample of operational audits conducted by the IRS and find that returns prepared by CPAs have fewer adjustments but determine that this correlation becomes negligible once income and sole-proprietorship status are controlled for.

Recently, the literature has advanced our understanding on both sides of the preparer-taxpayer market. On the supply side, Hansen and White (2012) provide experimental evidence that preparers respond to changes in penalties and enforcement rates, becoming less likely to take aggressive positions or to sign returns as penalties and enforcement increase. Batta, Finley, and Rosett (2019) also find that increases in competition among preparers lead to increased tax avoidance among their clients.

On the demand side, Kittl (2015) finds that high-income taxpayers pay less tax when they use professional tax preparers, whereas low-income taxpayers pay more. Rosenthal et al. (2023) survey taxpayers and find that those who use paid preparers put the highest weight on accuracy and less weight on minimizing their tax payment, relative to taxpayers who use software to prepare their returns. Among corporate taxpayers, Zwick (2021) finds that larger firms pay less tax when they use paid preparers; smaller firms do the opposite. Klassen, Lisowsky, and Mescall (2016) consider differences in tax aggressiveness by corporate taxpayers, finding that external preparers lead to more aggressive reporting, except when the same firm is used for auditing and tax preparation.

On the interaction between the demand and the supply sides, Battaglini et al. (2019) find that taxpayers self-select their tax accountant based on their risk tolerance and that tax accountants share with their customers information gleaned from audits of their other customers, potentially leading to higher evasion among their clients. Field evidence comes from Boning et al. (2020), who use a large-scale field experiment to show that when taxpayers are audited, their preparers update the risk and remit more tax to other clients.

Our paper contributes to this expanding literature in two ways. First, we study the longest time span and the most comprehensive sample thus far, increasing our confidence in the estimation of the preparers' impact on compliance in the recent period, when tax preparers increasingly compete not only with each other but also with tax-preparation software. Prior studies employed data from the United States from the late 1970s and early 1980s. Since then, the use of tax-preparation software has expanded significantly; such software is now used for about 30 percent of individuals' tax returns. Software also revolutionized the paid-preparer industry, enhancing productivity and potentially accuracy. Second, with the availability of line-item detail on the results of audits, as well as information on both the demographic characteristics of taxpayers and the type and market setting of paid preparers, we can identify the techniques paid preparers use and show that noncompliance is a result of features of both the demand and supply sides of the market.

The remainder of the paper proceeds as follows. Section II provides background on the use of tax preparers in the United States. Section III describes our empirical model, and Section IV relates the data. We present and explain our results in Section V. Section VI discusses some potential limitations of our findings, and Section VII concludes.

II. BRIEF BACKGROUND ON TAX PREPARERS

About 60 percent of individual income tax filers use a paid preparer to help with the filing of their return. Throughout the paper, we use *preparer* (without other adjectives) or *paid preparer* to refer to a professional, paid, human tax preparer. This definition excludes tax-preparation software that is used to assist with self-prepared returns (software is used in preparing about 30 percent of tax returns) or volunteer preparers through the VITA program (about 2 percent of tax returns). The IRS does not currently require licensing of preparers, though many hold certifications or licenses, including CPAs, lawyers, and IRS Special Enrolled Agents.[2] In 2011, the IRS began a program that required all tax preparers registered with the IRS to obtain a Preparer Tax Identification Number. Further, some preparers completing a Form 1040 for a client were required to obtain a license by passing a competency test

[2] An enrolled agent is a person who has earned special status to represent taxpayers before the IRS by passing a three-part examination covering individual and business taxes or through experience as an IRS employee. Enrolled agents are required to adhere to ethical standards and complete continuing education courses. See https://www.irs.gov/tax-professionals/enrolled-agents/enrolled-agent-information.

administered by the IRS, though certain preparers who were CPAs (or supervised by a CPA), attorneys, or enrolled agents were exempt. The federal licensing requirements were subsequently struck down in the District of Columbia District Court in 2013. However, some states, including California, Connecticut, Illinois, Maryland, Nevada, New York, and Oregon, require state licensing for tax preparers.[3]

Filers are more likely to use tax-preparation services as their income increases and as their return includes income with more complex reporting requirements, such as pass-through business income (see Klepper, Mazur, and Nagin, 1991). Long and Caudill (1987) find that taxpayers with high marginal tax rates are more likely to employ tax preparers. Slemrod and Sorum (1984) find that more-educated taxpayers spend less on tax-preparation services. Gunter (2019) shows that increased access to internet services moved filers toward software-assisted preparation, but the degree of substitution away from paid preparers due to increased software use is not clear. Benzarti (2020) finds that increases in complexity, such as itemization of deductions, increase the likelihood a taxpayer uses a professional preparer.

Because professional tax preparers are expected to have a better understanding of the tax code, penalties for noncompliance among preparers are often harsher than for individual filers. In particular, it is much more common for professional preparers to see jail time for misreporting income on a client's return than it is for the clients themselves (Hansen and White, 2012).

III. IDENTIFICATION STRATEGY

Identifying the causal impact of tax preparers on compliance is difficult for two reasons. First, our outcome variable (the size of audit adjustments) is subject to sample selection bias if the audit process is nonrandom, as is the case with operational audits conducted by tax authorities. Second, taxpayers' decisions to hire a tax preparer are endogenous and may be related to their demand for noncompliance. We solve the first issue by using data from randomized audits conducted through the NRP. To control for endogeneity in the method of preparation, we use an IV approach. The use of IVs differs from the prior literature on the role of paid preparers in tax compliance, such as Erard (1993), as those researchers deal with identification issues by using a structural estimator that relies on strong functional form assumptions, such as symmetry of error terms and the probability of self-preparation being unrelated to taxpayer characteristics. It is unlikely that such assumptions hold, especially with the rise in tax-preparation software, the use of which Gunter (2019) shows is strongly predicted by income and internet access.

Our IV models instrument for the decision to use a paid preparer using measures of peer effects that, we argue, plausibly affect the filer's choice of preparation method by affecting the costs of selecting a paid preparer. Peer effects driving familiarity with a technology, leading to lower adoption costs, have been supported in a number

[3] For additional details, see Ross, Wing, and Duncan (2022).

of domains, such as firm take-up of research-and-development tax exemptions (Kelchtermans, Neicu, and Teirlinck, 2020) and consumer use of residential solar power (Noll, Dawes, and Rai, 2014).

The instruments we employ include (i) the fraction of taxpayers in the filer's zip code who use a paid preparer, (ii) the fraction of taxpayers in the filer's workplace that use a paid preparer, (iii) the rates of e-filing, (iv) VITA preparer use in the filer's zip code, and (v) the EITC claim rate in the filer's zip code.[4] To construct these instruments, we use five-digit zip code areas, which are small geographic areas, and find considerable variation in the fraction of filers using professional preparation services across different zip codes.

For these to be valid instruments, they must satisfy the relevance criteria and the exclusion restriction. In terms of the relevance of these instruments to the choice of preparation method, instruments (i) and (ii) proxy for peer effects, with the idea that taxpayers may be more likely to use a preparer if their neighbors or coworkers use one as well. For example, assurances from friends about the productivity of professional tax-preparation services may lower the cognitive costs of employing a paid preparer, reducing the overall costs of that method relative to self-preparation.[5] Instruments (iii) and (iv) measure the availability of substitutes for paid preparers,[6] and (v) is an indirect proxy for the supply of preparation services in an area.[7] The availability of paid preparers, or their substitutes, is likely important in the filer's choice of preparation method. We provide empirical tests of the relevance of these instruments in Section V.

The exclusion restriction in our case is that there is no direct impact from our instruments on the tax-compliance decision of a particular filer except through their choice of preparation method. Our assumption is that peers are likely to share information on the tax-preparation method they use but are unlikely to share details on specific noncompliance strategies. Such a story is reasonable if there are social

[4] A third class of potentially interesting instruments that we are unfortunately unable to use are major life events such as the birth of a child, death of a spouse, unexpected change in job status, and so on. These can both change the complexity of the return and affect the taxpayer's cognitive workload, affecting their decision to hire a paid preparer in a plausibly exogenous way. However, we observe very few of these events in our audit sample, and they would not be able to provide us with the population-level estimates that our other instruments do.

[5] Appendix B (appendixes A and B are available online) provides a theoretical model, derived from Allingham and Sandmo (1972), that features a choice preparation method to illustrate how costs may affect the choice of preparation type but be unrelated to the degree of noncompliance conditional on that choice.

[6] Using the e-filer indicator that is recorded in our IRS data is an imperfect measure of the use of tax-preparation software. However, the vast majority of users of tax-preparation software do e-file.

[7] The use of the EITC claim rate as a proxy for the supply of tax-preparation services is based on Weinstein and Patten (2016), who find that the location of tax-preparer services is highly influenced by the number of filers who are potential EITC claimants, who in turn represent potential clients. In addition, Kopczuk and Pop-Eleches (2007) provide corroborating evidence, showing that the introduction of state e-filing programs, which led to an increase in the number of preparers, helped drive up EITC claim rates.

norms against tax noncompliance, which is the case in the United States (see, e.g., Bobek, Roberts, and Sweeney, 2007). Unfortunately, there does not exist a good empirical test for the exclusion restriction assumption. We therefore provide two illustrations of how this restriction might fail and how our empirical model would perform if the exclusion restriction were violated. Of course, this is not an exhaustive list, and because the reader might remain concerned about identification, we present OLS results alongside our IV estimates in Section V and provide a discussion of the potential biases in our estimates in Section VI.

One reason the exclusion restriction might fail is if areas with a higher share of professionally prepared returns also tend to have more preparers with higher rates of noncompliance (e.g., to get a competitive edge). Similarly, there could be unspecified unobservable factors that are positively correlated with individuals' proclivity for evasion and the demand for tax-preparation services in their area. In this case, we would expect our IV estimates of the impact of tax preparation on noncompliance to be upward biased.

Another concern might be that social networks are used for sharing advice on tax avoidance rather than (or in addition to) advice on which preparation method to use. In this case, our peer-effect instruments would be positively correlated with the error term in the noncompliance equation. It is difficult to test empirically whether this story is plausible, but we note that such a violation of the exclusion restriction would again tend to bias upward our IV estimates of the effect of paid preparers on audit adjustments.

To ameliorate any potential bias, our regression models control for other potential channels of correlation between tax-compliance decisions and the choice of tax preparation. To identify all plausible channels, we categorize the factors that correlate to both the instrument and the outcome variables into three groups:

i. Economic factors, such as income level, can affect both compliance and usage of tax preparation in a given zip code. We address economic factors by controlling for reported adjusted gross income (AGI) in the filer's zip code.[8]

ii. Cultural factors, such as the noncompliance norms in the area, can affect both compliance and usage of tax preparation. The audit data allow us to measure and control for the general noncompliance rate in the zip code, which proxies for norms of noncompliance. We use the rate of operational audits in the zip code to represent the general rate of noncompliance.[9] Our specifications also include four-digit zip-level fixed effects to control for time-invariant components of culture and norms.

[8] Note that we control for zip-level AGI but not the filer's reported/true AGI, because these may be mechanically related to the audit adjustments that are our outcome variable.

[9] From the IRS Data Book (IRS, 2021), Table 17, we find that 86 percent of individual audits result in a positive adjustment to tax liability. Targeted audits thus represent a reasonable proxy for noncompliance and also serve as an important control for enforcement rates, which may affect taxpayers' compliance decisions, as in the canonical Allingham and Sandmo (1972) model.

iii. Market structure, such as the degree of competition among tax preparers in the area, can affect both compliance and usage of tax preparation. For example, as noted above, increased competition might drive tax preparers to be more aggressive. More competition might also drive down prices, affecting the quantity of preparation services demanded. We control for market concentration by including a measure of the concentration of tax preparers in the filers' commuting zone, the Herfindahl–Hirschman index (HHI).

Because, as noted in ii above, when we include four-digit zip code fixed effects, we identify preparer's effects on compliance through the change in preparer use rates over time within four-digit zip code areas. Thus, concerns about the exclusion failing must not just involve a cross-sectional direct relationship between the use of tax preparation in a zip code and tax compliance of an individual taxpayer but must be related to within four-digit zip code changes in the use of tax preparation directly affecting within four-digit zip codes changes in compliance.

Our first-stage model estimates the likelihood that filer i in zip code z at time t uses a paid preparer as

$$\begin{aligned} 1\{Use\ Preparer\}_{i,z,t} = {} & \alpha + \rho_1 FracPreparers_{z,t} + \rho_2 EfileRate_{z,t} \\ & + \rho_3 VITA\_Rate_{z,t} + \rho_4 EITC\_Rate_{z,t} \\ & + \rho_5 \text{Workplace\_Preparers}_{z,t} + \boldsymbol{\beta X}_{i,z,t} + \eta_t + \mu_z + u_{i,z,t}. \end{aligned} \tag{1}$$

We include a set of tax-year fixed effects, represented by η_t, four-digit zip code fixed effects, μ_z, and a set of time-varying controls, $\boldsymbol{X}_{i,z,t}$. The time-varying controls include filing status, gender of the primary filer, linear and quadrat terms for age, the number of dependents on the return, and five-digit zip code–level controls (average AGI, log of population, the rate of nonrandom operational audits, and the Herfindahl index for tax-preparer concentration).[10] The key identifying assumption we make is that the excluded instruments are only related to an individual tax filer's compliance through its effects on her likelihood of using a preparer.

In the second stage of our model, we regress the dollar amount of audit adjustment found in the NRP audit on the fitted value for preparer use and our set of exogenous control variables:

$$Audit\ Adjustment_{i,z,t} = a + \phi \left\{ Use\ \widehat{Preparer} \right\}_{i,z,t} + \boldsymbol{\gamma X}_{i,z,t} + \delta_t + \mu_z + \varepsilon_{i,z,t}. \tag{2}$$

We estimate the model given in Equation (2) using the audit adjustment amount in levels (as opposed to its logarithm) because it can take on positive or negative values. The main coefficient of interest is ϕ, the effect of the use of a preparer

[10] We exclude from these regressions variables that are potentially endogenous to the use of a preparer, such as the amount of reported income on the filers' returns and the sources of reported income, or the use of certain tax credits, such as the EITC.

on tax compliance. This term measures a local average treatment effect, which is the effect of preparers on the audit adjustments of filers who were at the margin of using a preparer or not and for whom peers may be decisive.

IV. DATA

Our primary data source is the NRP, which began in 2001 as a replacement for the TCMP. As such, it serves as the basis for measures of the *tax gap* (the total amount of taxes not paid due to noncompliance; IRS, 2019). After an initial wave in 2001, the NRP began selecting returns for audit annually, starting in 2006 and continuing to the present. NRP audits differ from operational audits conducted by the IRS. NRP audits are generally more thorough, covering all items on the filer's tax return. Operational audits, in contrast, often target items that appear to be at issue.

In our analysis, we use NRP waves for tax years 2006–2014. Each wave comprises about 15,000 observations from a stratified random sample of the population of filers. The NRP oversamples groups of particular interest for tax compliance, such as high-income filers or those claiming the EITC. Using the sampling weights, we construct a sample of filers that is representative of the population of filers. Because of the stratified nature of the NRP sampling, we use the sample weights in all of our main analyses, both tabulations of the data and our econometric models. This allows us to interpret values as averages across the population of filers, as opposed to the average across the NRP sample (which is what unweighted estimates would provide). However, when reporting the number of observations in our tables, we report the unweighted number of observations. We classify a return as having used a paid preparer if identifying information for a non-VITA preparer is present on the original return.[11] For our baseline analysis, we drop the 2 percent of returns that use a VITA preparer and thus compare those with a paid preparer to those who self-prepare their returns.[12]

We derive our dependent variables from the IRS agents' adjustments to line items on the taxpayers' 1040s that result from the NRP audits. We therefore define "noncompliance" through the size of these adjustments and "true income" as reported income plus the recommended IRS adjustment. Note that these are not perfect measures of compliance or true income, as there are in some cases legitimate disagreements over reported amounts, and there is some noise in the audit process.[13] All currency values are in constant 2012 dollars.

[11] Note that this means we are unable to identify so-called ghost preparers, who prepare a return for money but do not identify themselves on the return. We discuss how this may bias our results in Section VI.

[12] We include returns that use a VITA preparer when we turn our analysis to examine the impact of VITA preparers on compliance.

[13] Doran (2009) makes the case that penalties for noncompliance could be a better measure of evasion than the amount of the postaudit adjustment itself. Unfortunately, our data do not allow us to observe the final penalties imposed on taxpayers. Unless the noncompliance found upon audit is overturned, the penalty rate is 20 percent of the underpaid tax amount plus interest. The exceptions

The second data source we draw upon is the population of tax returns 2006–2014. We use these data to compute zip code–level measures that we use in our IV approach, our workplace preparer use IV, and additional control variables. In computing our IVs, at the zip code or employer (EIN) level, we exclude the individual filer from the calculation of the instrument to avoid making the instrument endogenous to the filer's decision to use a preparer.

Our IV that proxies for peer effect through the workplace is the fraction of coworkers using a paid preparer. We compute this by taking the EIN from the primary filer's Form W-2 statement, selecting all returns that have W-2s from the same EIN, and computing the fraction of those returns that use a paid preparer. For self-employed taxpayers, for whom we do not have a W-2 with an EIN on it, we follow the method of Angrist, Lavy, and Schlosser (2010) for nonrandom missing values for instruments and use imputed values for the workplace preparer use instrument from the rest of the sample.

We measure the degree of observed competition among tax preparers in a commuting zone (CZ) by computing the HHI, using the number of returns prepared by a given tax-preparation entity within that CZ.[14] In particular,

$$HHI_z = \sum_{n=1}^{N_z} s_{n,z}^2,$$

where $s_{n,z}$ is the share of tax returns in CZ z prepared by tax-preparation entity n (identified by its EIN). The total number of firms in the CZ, N_z, is defined as the total number of firms that prepare returns for filers from CZ z:

$$s_{n,z} = \frac{\textit{number returns from CZ z prepared by EIN n}}{\textit{number returns from CZ z using paid preparer}}.$$

Note that, in this measure, the numerator does not include all returns by EIN n, just those from the particular commuting zone.

Table 1 compares mean amounts of taxable income, tax liability, mean age, and rates of EITC claims, as well as the presence of different schedules across filers who use paid preparers, those who use a VITA preparer, those who self-prepare, and all filers.[15] The means computed here are not conditional on having nonzero values and are measured as postaudit values. We find that filers who use tax preparers tend to make more income, with an average taxable income of $58,790 for those using preparers compared with $39,450 for those not using preparers. Those using VITA

to this are cases of clearly fraudulent reporting, which can carry more significant penalties including imprisonment, but these are extremely rare (less than 750 per year according to the IRS Databook [IRS, 2021]).

14 See https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas.

15 We include descriptive statistics on the geographic-level control variables in Appendix A.

Table 1

NRP Sample Means

	Filers Using a Paid Preparer	Filers Using a VITA Preparer	Filers Self-Preparing	All Filers
Taxable income				
Nonzero mean ($)	58,790	18,461	39,450	50,251
Total tax (%)	79.00	59.30	78.24	78.28
Nonzero mean ($)	12,503	2,475	6,766	10,010
Fraction with wage and salary income (%)	80.54	70.72	88.93	83.76
Nonzero mean ($)	54,029	18,996	45,939	49,917
Fraction with Sch C income (%)	20.35	6.02	12.90	17.02
Nonzero mean ($)	13,916	3,308	6,447	11,531
Fraction with Sch D income (%)	22.87	11.03	14.35	19.15
Nonzero mean ($)	22,808	593	3,964	16,791
Fraction with Sch E income (%)	17.84	2.23	6.24	12.79
Nonzero mean ($)	32,338	2,483	7,150	27,228
Fraction claiming EITC (%)	15.75	20.23	12.53	14.53
Nonzero mean ($)	2,414	1,491	1,905	2,208
Fraction with itemized deductions (%)	34.35	10.14	26.57	30.68
Nonzero mean ($)	29,437	15,577	22,466	26,883
% using paid preparer	100.00	0	0	57.19
CPA	21.43	0.00	0.00	12.26
Enrolled agent	7.06	0.00	0.00	4.04
Large preparer	10.35	0.00	0.00	5.92
Attorney	0.47	0.00	0.00	0.27
Other or unspecified preparer	60.69	0.00	0.00	34.71
Fraction using VITA preparer (%)	0.00	100.00	0	2.07
% with an upward adjustment to tax liability	44.35	18.20	36.56	40.63
Nonzero mean ($)	906	91	477	714
Age	47	54	42	45
Fraction married filing jointly (%)	42.00	24.2	33.25	38.07
Fraction head of household (%)	11.10	9.02	8.35	9.94
Number of dependents (mean)	0.6	0.2	0.5	0.5
Fraction with male primary filer	66.16	46.39	61.55	63.87
Observations				
Unweighted	75,009	1,085	29,076	105,170
Weighted	628,986,050	22,815,461	447,963,587	1,099,765,098

Note: Data come from the IRS National Research Program, 2006–2014. Statistics are computed using NRP sampling weights. Means are not conditional on nonzero values, and income, tax, credit, and deduction items are measured using preaudit values. All dollar values are in 2012$.

preparers have an average taxable income of $18,461. The proportion of filers who claim the EITC is higher for those using preparers, consistent with the idea that complexity of one's return may play a role in the use of a paid preparer. Indeed, those with paid preparers are much more likely to have business income reported on Schedule C or E, and to have significantly more income from those sources, than filers who do not use a paid preparer.

We measure compliance using audit adjustments found through NRP audits. Table 2 shows compliance rates of those who use paid preparers and those who do not, computed from adjustments to individuals' tax returns from NRP audits. Note that mean values reported in the first columns of each panel are conditional on reporting a nonzero value for that line item and are measured as preaudit (i.e., reported) values. Rates of compliance, as measured by the fraction of filers with nonzero adjustments, are quite similar across these two groups for wages and salaries. However, if we look at income that is more complicated to report and often with less third-party reporting, such as income reported on Schedules C, D, and E, we find significant differences between filers using preparers and those who do not. Filers who do not use preparers have higher rates of adjustment to their reported income. Income from Schedule E, which includes S-corporation and partnership income, is adjusted on 51 percent of returns filed using a paid preparer and 68 percent of returns filed without a paid preparer. The difference is similar for Schedule D, which includes capital-gains income, which is adjusted just 24 percent of the time for those using a paid preparer but 41 percent of the time for those not using a paid preparer. This suggests higher noncompliance rates by those who do not use a paid preparer. Patterns of over- and underreported income are similar across these two groups, though rates of misreporting are much higher for sources of income with less third-party documentation (such as Schedule C income) than for those with more third-party documentation (such as wages and salaries).

However, when we look at the dollar amounts of income that is underreported, those using paid preparers have much larger amounts. For example, the mean amount by which Schedule D income is underreported by those using paid preparers is $8,165, compared with $3,265 by those who do not use a paid preparer. Likewise, the mean amount by which Schedule E income is underreported is $10,191 by those using a paid preparer and $7,475 by those who do not use a preparer. When considering these underreported income amounts as a fraction of mean income for filers using a given method of preparation, the results are flipped. For example, the mean amount of underreported Schedule E income is about 68 percent of mean Schedule E income for those self-preparing their returns and about 32 percent for those using a paid preparer. Higher incomes can mechanically lead to larger underreporting because the scope to underreport income is larger. Still, while the compliance rates in Table 2 do not show causal evidence of the role of preparers in tax compliance, the patterns are consistent with the results of prior work, such as Klepper and Nagin (1989), who find that tax preparers lead to fewer mistakes but more aggressive reporting when there is ambiguity in the law.

Table 2

Summary of Audit Adjustments

	Filers Using a Paid Preparer				Filers Using a VITA Preparer				Filers Who Self-Prepare			
	Preaudit Income	Nonzero Audit Adjustment	Underreported Income	Overreported Income	Preaudit Income	Nonzero Audit Adjustment	Underreported Income	Overreported Income	Preaudit Income	Nonzero Audit Adjustment	Underreported Income	Overreported Income
Taxable income ($)	47,528	6,553	8,040	−2,953	11,325	1,531	2,100	−1,396	31,785	4,147	5,527	−1,763
Nonzero fraction (%)	76	69	60	9	60	42	35	7	78	60	48	11
Total tax ($)	9,884	1,672	2,043	−773	1,469	361	501	−291	5,300	994	1,304	−412
Nonzero fraction (%)	74	69	60	9	57	39	32	7	74	60	49	11
Wages and salaries ($)	43,544	2,630	4,546	−7,351	13,436	495	1,241	−4,390	40,915	65	3,358	−6,640
Nonzero fraction (%)	80	6	5	1	71	5	4	1	89	7	5	2
Sch C income ($)	2,826	9,544	11,612	−4,902	206	3,774	4,981	−1,888	808	7,745	9,457	−3,350
Nonzero fraction (%)	19	81	71	10	5	57	47	10	11	86	75	12
Sch D income ($)	5,216	4,475	8,165	−5,606	65	270	932	−997	569	1,706	3,265	−2,057
Nonzero fraction (%)	21	24	18	7	9	29	19	10	12	41	29	12
Sch E income ($)	5,741	5,878	10,191	−8,992	54	7,528	12,057	−1,144	438	4,900	7,475	−3,548
Nonzero fraction (%)	17	51	39	11	2	33	22	11	5	68	52	16
Earned Income Tax Credit ($)	488	−1,308	502	−1,584	342	−726	332	−1,005	301	−1,081	385	−1,333
Nonzero fraction (%)	21	50	7	43	23	30	6	24	16	44	6	38
Itemized deductions ($)	10,628	−3,077	3,642	−4,856	1,747	−1,991	2,803	−4,101	6,431	−3,264	5,005	−5,302
Nonzero fraction (%)	37	78	16	62	12	68	21	48	29	76	15	61

Note: This table reports the measures of compliance found in NRP data from tax years 2006–2014. The first four columns report statistics summarizing tax compliance among tax filers who used a paid preparer in filing their tax return. The first column reports means by income and deduction sources and the fractions with those sources of income. Means are conditional on reporting nonzero values, and preaudit values (i.e., values based on reported income) are used. The second column reports the average additional tax liability request during NRP audits (often called audit adjustment), conditional on nonzero adjustment. The third and fourth columns report the average underreported and overreported incomes, conditional on underreporting or overreporting. The final four columns report these same statistics for tax-filing units that did not use a paid preparer. All dollar values are in 2012$.

V. RESULTS

A. Do Paid Preparers Improve Compliance?

Table 3 presents estimates from the IV and OLS models using a sample of all NRP filers and, for the IV models, our set of five excluded instruments. We estimate the impact of paid preparers on two different outcomes: audit adjustments to taxable income and audit adjustments to total tax liability. Total tax liability is in many ways the ultimate measure of a tax preparer's efforts. However, it can sometimes be difficult to compare changes in tax liabilities across individuals because of different tax bracket cutoffs and rates. Therefore, we also consider taxable income, which incorporates most of the significant avenues for misreporting but is calculated before income tax rates are applied. Columns 1 and 3 relay estimates from our preferred IV model, while Columns 2 and 4 present OLS estimates. All specifications include time and four-digit zip code fixed effects, time-varying individual, and five-digit zip-level controls.[16] A summary of the first-stage regression results is at the bottom of Table 3 and shows that the excluded instruments, in particular the fraction of filers in the zip code area using paid preparers and the local EITC claim rate,[17] are strong predictors of an individual filer's use of a preparer.[18]

In Columns 1 and 3, audit adjustments to taxable income are estimated to be $3,903 higher when a paid preparer is used to file the return, and audit adjustments to total taxes are $518 larger when a paid preparer is used.[19] The average adjustment to total taxes across filers in the NRP who self-prepare their returns is $596,[20] meaning that preparers increase noncompliance by about 87 percent.[21]

[16] Many zip codes appear only a handful of times in our data, which requires us to drop much of the population if we wish to use five-digit zip code fixed effects. In this specification, we base our fixed effects on the first four digits of the zip code instead.

[17] Figure A1 shows the results of two placebo tests on the excluded instrument. Figure A1*A* shows the distribution of Z-scores of the coefficient on the preparer-usage rate in the first-stage regression from 10,000 simulations where the zip code preparer usage rate was drawn randomly. The distribution is centered around zero, signaling that preparer usage rates are important in the first stage and their significance is not spurious. Figure A1*B* shows the distribution of Z-scores from the second-stage regression where preparer use is drawn randomly. The distribution of these Z-scores is centered around zero, showing that predicted preparer use is important in determining audit adjustments.

[18] The Cragg-Donald Wald *F* Statistic is more than 4.3 million, much higher than the Stock-Yogo critical values for reasonable levels of significance (e.g., the 10 percent maximal IV size cutoff is 26.87).

[19] We have also estimated specifications that included controls for reported AGI and its square, true AGI and its square, the fraction of taxpayers receiving EITC, or the mean EITC amount received in the zip code. The results from these specifications were quantitatively very similar to those found in Table 3.

[20] Table A5 presents results using each of our instruments individually in a specification, as well as using only our local and workplace preparer usage instruments in combination. With the exception of the specification in which the VITA usage instrument is used in isolation, the results across these specifications are qualitatively similar to those in the IV specification presented in the body of the paper.

[21] From the average of $596 among self-prepared returns, we multiply the average nonzero adjustment amount in Table 2 ($994) by the fraction of filers with a nonzero adjustment (60 percent).

Table 3

Parameter Estimates, Regression of Tax Preparers on Audit Adjustments

	Taxable Income		Total Tax	
	IV	OLS	IV	OLS
Paid preparer use	3,902.78***	884.29***	518.23***	150.91***
	(808.27)	(274.24)	(104.38)	(33.82)
Age	195.25***	50.56***	192.89***	50.05***
	(14.36)	(4.03)	(14.02)	(3.95)
Age squared	−2.15***	−0.55***	−2.02***	−0.53***
	(0.15)	(0.04)	(0.14)	(0.04)
Primary filer male	536.86***	195.16***	613.02***	211.66***
	(105.51)	(30.50)	(101.40)	(29.12)
Number of kids	173.55**	41.76	257.79***	60.01**
	(78.91)	(25.87)	(74.93)	(25.59)
Mean AGI	0.01***	0.00***	0.01**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
ln(Population)	19.33	30.28	−26.52	20.35
	(77.33)	(23.88)	(75.22)	(23.58)
Audit rate	57,236.37***	12,170.66**	67,365.12***	14,365.40***
	(16,154.81)	(5,389.59)	(15,496.29)	(5,176.24)
Preparer HHI	−1,505.75	−647.36	864.14	−133.85
	(5,802.37)	(1,575.25)	(5,699.01)	(1,539.94)
Schedule C	4,741.68***	1,533.90***	5,002.49***	1,590.42***
	(217.78)	(78.24)	(214.74)	(76.08)
Schedule D	−227.52	−157.44**	−27.77	−114.16
	(210.26)	(71.77)	(210.00)	(70.04)
Schedule E	3,503.73***	967.38***	4,129.41***	1,102.95***
	(343.32)	(116.53)	(302.70)	(108.27)
Earned Income Tax Credit	−3,315.09***	−847.11***	−3,069.01***	−793.79***
	(143.90)	(50.79)	(136.62)	(48.13)
Itemizer	233.06	67.23	340.97	90.62
	(209.42)	(76.31)	(208.33)	(76.24)
Filing status controls	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes
Four-digit zip code FEs	Yes	Yes	Yes	Yes
N	103,385	103,385	103,385	103,385
N, weighted	1,057,489,371	1,057,489,371	1,057,489,371	1,057,489,371

Table 3 (Continued) Parameter Estimates, Regression of Tax Preparers on Audit Adjustments

	Taxable Income		Total Tax	
	IV	OLS	IV	OLS
	1st-Stage Results		1st-Stage Results	
Fraction use preparers	0.74***		0.74***	
	(0.08)		(0.08)	
Local e-file use	−0.01		−0.01	
	(0.06)		(0.06)	
Local VITA use	0.69***		0.69***	
	(0.22)		(0.22)	
Local EITC claim rate	0.23***		0.23***	
	(0.06)		(0.06)	
Workplace preparer use	0.40***		0.40***	
	(0.02)		(0.02)	
R^2	0.213		0.213	
N	103,385		103,385	
N, weighted	1,057,489,371		1,057,489,371	

Note: This table reports the results of a regression of audit adjustments on an indicator for the use of a paid preparer and a set of control variables. Columns 1 and 3 show estimates from OLS models. IV models in Columns 2 and 4 instrument for preparer use using the fraction of taxpayers in the filer's zip code using paid preparers, the fraction of those in the filer's workplace using paid preparers, the fraction of filers who use a VITA preparer in the filer's zip code, the EITC claim rate in the filer's zip code, and the rate of e-filing in the filer's zip code. Demographic controls include an indicator for dependents claimed, whether the primary filer is male, filing status, age, and age squared. Zip code–level controls include the log of population, the operational audit rate, tax-preparer market concentration, and average AGI. Schedule C, Schedule D, and Schedule E are indicator variables representing the presence of these forms on the taxpayer's return. Indicator variables for Earned Income Tax Credit represent EITC claim status and whether the taxpayer itemizes deductions. Standard errors clustered at the zip code level are reported in parentheses below the point estimates. *N* denotes the number of observations. Asterisks denote significance at the 1% (***) and 5% (**) levels. All dollar values are in 2012$.

To see the importance of controlling for selection into the use of a paid preparer, one can compare the IV estimates to the analogous OLS estimates in Columns 2 and 4. The finding in the OLS model is that audit adjustments to taxable income are about $884 larger if a paid preparer is used, as compared with the estimate of $3,903 from the IV model. OLS estimates of adjustments to tax liability are also less than a third of the value of the IV estimates. Hausman tests confirm that these point estimates are significantly different at the 95 percent level. Thus, there is strong evidence that preparer use is not only endogenous but also in such a way that it tends to bias the estimated coefficients toward zero. This suggests that the taxpayers hiring paid preparers are those who would be unwilling or unable to prepare their own return in an aggressive manner.

Estimates in Table 3 are from weighted least squares models where the NRP sampling weights are used to account for the stratified random sample. Solon, Haider, and Wooldridge (2015) note that sampling weights may not be necessary when estimating causal effects and further note that a comparison between the parameter estimates from weighted and unweighted regressions maybe useful to learn about heterogeneous treatment effect. We therefore also estimate the specifications in Table 3 but without the NRP sampling weights. Results are reported in Appendix A and show that the coefficients on preparer use from the unweighted regression models are more than three times as large as they are in the weighted regressions (in both the IV and the OLS estimates). Because the NRP oversamples high-income taxpayers (as well as EITC claimants), we take this finding as suggestive evidence of heterogeneous treatment effects. We explore these more in Sections V.B and V.D, where we focus on low-income filers and heterogeneous responses across the income distribution, respectively.

Table 4 replicates the adjustments to taxable income results of Table 3 and then shows the relationship between paid preparers and audit adjustments across various income and deduction items. The last six columns of Table 4 are estimated on samples that condition the filer having income or deductions of the given type. The only income source that appears significantly affected by preparer usage is Schedule C income, which has adjustments that are more than $9,900 larger among filers using paid preparers. However, we find adjustments to EITC claims to be significantly different across self-prepared and professionally prepared returns. Adjustments to the EITC are an additional $171 lower for returns that are professionally prepared relative to self-prepared returns (note that a negative adjustment to the EITC results in higher tax liability). Panel *B* presents the OLS results, which have the same sign as the IV results but smaller point estimates.

B. Do Volunteer Preparers Improve Compliance?

An important factor in determining whether or not to use a paid preparer is likely to be the amount of income they will report relative to what would be reported if the return is self-prepared.[22] One way to attract paying clients is to maximize their refund or minimize taxes paid, which can lead to paid preparers pushing the boundaries of what the IRS deems appropriate and resulting in larger adjustments upon audit. In this section, we test that hypothesis by comparing audit adjustments when using a paid preparer with those from returns filed with the help of a skilled volunteer preparer.

The VITA program provides free tax-preparation services to qualifying taxpayers. These are taxpayers with low-to-moderate income, senior citizens, the disabled, and those with limited English language skills. VITA preparers often work a few hours a week during the main tax filing season (February to April). These

[22] This is discussed in our theoretical model in Appendix B.

Table 4

Regression Estimates from Tax Preparers on Audit Adjustments by Income Source

		Conditional Sample					
	Taxable Income	Wages	Sch C	Sch D	Sch E	EITC	Itemized Deductions
IV							
Paid preparer use	3,902.78***	185.50	9,910.20**	711.53	−2,396.01	−171.17*	−1,009.04
	(808.27)	(176.21)	(4,418.48)	(2,008.72)	(4,880.12)	(101.65)	(2,291.60)
N	103,385	80,714	39,315	39,024	36,685	13,305	54,222
N, weighted	1,057,489,371						
OLS							
Paid preparer use	884.29***	94.49***	1,471.29***	78.49	−82.60	−39.18***	−43.49
	(274.24)	(27.57)	(369.20)	(225.09)	(284.07)	(14.02)	(345.00)
N	103,385	80,714	39,315	39,024	36,685	13,305	54,222
N, weighted	1,057,489,371	890,238,447	185,000,303	204,098,401	139,579,781	155,085,356	334,784,668

Note: This table reports the results of a regression of audit adjustments on an indicator for the use of a paid preparer and a set of control variables. Conditional samples include only filers who report a nonzero value for the given income course. IV models instrument for preparer use using the fraction of taxpayers in the filer's zip code using paid preparers, the fraction of those in the filer's workplace using paid preparers, the fraction of filers who use a VITA preparer in the filer's zip code, the EITC claim rate in the filer's zip code, and the rate of e-filing in the filer's zip code. All models include four-digit zip code fixed effects, year effects, demographic controls, time-varying zip code–level controls, and indicator variables for the presence of Schedule C, Schedule D, or Schedule E income on the taxpayer's return, claiming the Earned Income Tax Credit, and itemizing deductions. Demographic controls include an indicator for dependents claimed, whether the primary filer is male, filing status, age, and age squared. Zip code–level controls include the log of population, the operational audit rate, tax-preparer market concentration, and average AGI. Standard errors clustered at the zip code level are reported in parentheses below the point estimates. *N* denotes the number of observations. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels. All dollar values are in 2012$.

volunteers typically meet with taxpayers in community centers, libraries, shopping malls, or other public locations. VITA preparers undergo training and are supported with tax-preparation software. However, there are situations that the VITA preparers are not allowed to help with, such as depreciation and certain types of business income. Taxpayers who have such income and deduction sources cannot use the VITA program.

As with the use of paid preparers, we need to control for the selection of filers into the use of a VITA preparer. To do this, we employ the same set of excluded instruments that we use in our other models: the fraction of filers using a paid preparer in the zip code and in the taxpayer's workplace, the fraction of filers using a VITA preparer in the zip code, the fraction e-filing, and the local EITC claim rate.

Panel *A* in Table 5 reports the results from estimating IV models for paid preparer use and VITA use on adjustments to income, its components, and itemized deductions.[23] These estimates show positive effects of paid preparers on audit adjustments (as we find in the sample without VITA filers) and positive coefficients on the VITA preparer indicator, although these are measured with very large standard errors.[24] We find issue with instrumenting for VITA use across the full sample. This may be because the restrictions on VITA usage preclude many filers from ever using a VITA preparer; however, the predicted value from the first-stage regression may be positive. Panel *B* reports the results when we limit our sample to filers whose postaudit AGI is found to be under $70,000. This eliminates a large number of those VITA-ineligible filers. We now see that the impacts of the VITA preparers on adjustments to taxable income are negative and more precisely estimated. In the case of the IV models, these estimates are not statistically different from zero. But the OLS models are more precise and reveal negative point estimates on audit adjustments when VITA preparers are used that are statistically different from zero. The coefficients on paid preparer use remain statistically significant and positive in both the IV and the OLS models. Thus, we can say that VITA-eligible filers who take advantage of the program have audit adjustments that are much smaller than those who use a paid preparer, although perhaps not different from those who self-prepare. Because VITA volunteers do not face market pressure to compete for clients, they do not face the same pressures to push the boundaries as paid preparers. It is also possible that the type of individual who becomes a VITA volunteer is different from one who becomes a paid preparer and is inclined to give more conservative tax-preparation advice.

[23] Because VITA preparers cannot handle certain types of income on Schedules C, D, and E, we do not estimate the effects of VITA preparers on those income sources.

[24] OLS estimates are more precise and suggest filers using VITA preparers have smaller audit adjustments than self-prepared returns, but this should be interpreted with caution given selection into VITA use.

Table 5

Parameter Estimates, Regression of VITA, and Paid Preparer Usage on Audit Adjustments

	Taxable Income	Total Tax	Conditional Sample: Wages	Conditional Sample: EITC
Panel A: All Taxpayers				
VITA use, IV	4,382.95	1,894.90	−1,879.75	59.55
	(4,907.68)	(1,416.58)	(1,369.19)	(530.21)
Paid preparer use, IV	3,918.62***	911.58***	98.74	−150.03
	(859.51)	(288.89)	(177.30)	(118.40)
N	104,462	104,462	81,531	13,737
VITA use, OLS	−308.56*	−18.00	83.07*	84.17***
	(176.26)	(52.34)	(44.13)	(30.13)
Paid preparer use, OLS	521.65***	151.43***	95.21***	−39.05***
	(103.73)	(33.60)	(27.53)	(13.86)
N	104,462	104,462	81,531	13,737
N, weighted	1,080,102,255	1,080,102,255	906,176,925	159,699,974
Panel B: Low-Income Taxpayers Only				
VITA use, IV	−1,161.53	−445.24	753.74	59.66
	(1,950.38)	(334.84)	(705.82)	(530.18)
Paid preparer use, IV	1,901.58***	338.05***	405.85***	−149.99
	(385.42)	(71.50)	(127.90)	(118.40)
N	54,286	54,286	40,651	13,736
VITA use, OLS	−372.79***	−69.32***	44.76	84.17***
	(92.78)	(19.20)	(39.50)	(30.13)
Paid preparer use, OLS	360.20***	76.52***	98.28***	−39.05***
	(49.32)	(10.20)	(21.44)	(13.87)
N	54,286	54,286	40,651	13,736
N, weighted	802,944,554	802,944,554	659,935,652	159,699,108

Note: This table reports the results of a regression of audit adjustments on an indicator for the use of a VITA preparer, an indicator for paid preparer use, and a set of control variables. IV models instrument for preparer use using the fraction of taxpayers in the filer's zip code using paid preparers, the fraction of those in the filer's workplace using paid preparers, the fraction of filers who use a VITA preparer in the filer's zip code, the EITC claim rate in the filer's zip code, and the rate of e-filing in the filer's zip code. Demographic controls include an indicator for dependents claimed, whether the primary filer is male, filing status, age, and age squared. Zip code controls include the log of population, the operational audit rate, tax-preparer market concentration, and average AGI. Standard errors clustered at the zip code level are reported in parentheses below the point estimates. *N* denotes the number of weighted observations. Asterisks denote significance at the 1% (***) and 10% (*) levels. All dollar values are in 2012$.

C. What Techniques Do Preparers Use?

In the preceding sections, we show that paid preparers increase the rate of noncompliance on tax returns. This result does not appear to be driven by third-party preparers in general, as we find that returns prepared by VITA volunteers have lower noncompliance rates than returns with paid preparation. Furthermore, as Table 4 indicates, noncompliance by paid preparers is not consistent across all parts of the tax return. Income from Schedule C and EITC claims are the two major areas in which audit adjustments significantly differ between filers who self-prepare and those using paid preparers. In this section, we explore in more detail the components of Schedule C income to identify more precisely the channels through which preparers may drive higher noncompliance among taxpayers with sole-proprietor income. Note that the results presented in Table 6 condition on the taxpayer including a Schedule C income, but we do not condition on the reporting of specific line items on this schedule. This is because we want to consider all margins over which the preparer may influence their client within the reporting of Schedule C income. These margins include both the intensive margin (how much to report) and the extensive margin (e.g., whether to report a certain type of income or deduction at all).

Table 6 applies the model from Equation (2) to the major components of Schedule C income using the sample of filers that report any Schedule C income. These components are gross receipts, returns and allowances, cost of goods sold, other income total expenses, and business home use. We find that the most significant adjustments to Schedule C come from expenses, which tend to be overstated by about \$6,100 more by those who use paid preparers than those who do not. There is little third-party documentation provided to the IRS for cross-referencing expense items reported on the tax return, and it is well documented that sources of income with little or no third-party reporting are much more likely to exhibit noncompliance.

D. Is Noncompliance Demand-Driven?

If this noncompliance is demand-driven, then we should find more demanding clients hiring tax preparers who underreport their tax liability to a greater degree. To test this, we split the sample into several groups based on known predictors of tax compliance. First, we consider gender differences by comparing taxpayers who are single male filers with taxpayers who are single female filers.[25] Next, we estimate regression models that allow the effect of paid preparers to vary across age. Finally, we compare filers of different income levels.

Table 7, Columns 1 and 2 show estimates from IV and OLS models of Equation (2) on a sample of single filers with an interaction of tax-preparer usage and gender. While tax preparers result in larger audit adjustments to taxable income for both

[25] We exclude head-of-household and married-filing-separately filers from these two subsamples, restricting them to only those who file as single. We find gender by merging demographic characteristics from Social Security Administration files onto our tax-return data.

Table 6

Schedule C Adjustments, Revenues, and Expenses

	Net Income	Gross Receipts	Returns and Allowance	Cost of Goods Sold	Other Income	Expenses	Business Home Use
IV							
Paid preparer use	9,910.20**	4,583.24	673.80	310.11	232.45	−6,164.72***	3.68
	(4,418.48)	(7,463.69)	(476.79)	(6,228.04)	(492.95)	(1,707.17)	(189.34)
OLS							
Paid preparer use	1,471.29***	1,255.68	31.51	85.35	27.28	−409.38***	106.95***
	(369.20)	(908.43)	(27.11)	(833.56)	(28.69)	(151.73)	(20.79)
N	39,315	39,315	39,315	39,315	39,315	39,315	39,315
N, weighted	185,000,303	185,000,303	185,000,303	185,000,303	185,000,303	185,000,303	185,000,303

Note: This table reports the results of a regression of audit adjustments on an indicator for the use of a paid preparer and a set of control variables separately by line items on Schedule C using a sample of filers who reported nonzero income on Schedule C. The IV models instrument for preparer use using the fraction of taxpayers in the filer's zip code using paid preparers, the fraction of those in the filer's workplace using paid preparers, the fraction of filers who use a VITA preparer in the filer's zip code, the EITC claim rate in the filer's zip code, and the rate of e-filing in the filer's zip code. Demographic controls include an indicator for dependents claimed, whether the primary filer is male, filing status, age, and age squared. Zip code–level controls include the log of population, the operational audit rate, tax-preparer market concentration, and average AGI. Schedule C, Schedule D, Schedule E, Earned Income Tax Credit, and Itemizer represent indicator variables for the presence of these forms on the taxpayer's return, EITC claim status, and itemization of deductions. Standard errors clustered at the zip code level are reported in parentheses below the point estimates. *N* denotes the number of observations. Asterisks denote significance at the 1% (***) and 5% (**) levels. All dollar values are in 2012$.

Table 7

Parameter Estimates, Regression of Paid Preparer Usage on Audit Adjustments to Taxable Income by Demographics

	Gender		Age	
	IV	OLS	IV	OLS
Paid preparer use by men	5,471.96***	1,051.06***	–	–
	(1,268.63)	(204.17)	–	–
Paid preparer use by women	2,501.94***	−23.51	–	–
	(900.10)	(127.98)	–	–
Paid preparer use	–	–	−13,193.79	1.30
	–	–	(12,504.37)	(2,324.51)
Paid preparer use × age	–	–	726.25	53.69
	–	–	(536.52)	(80.52)
Paid preparer use × age squared	–	–	−7.08	−0.72
	–	–	(5.53)	(0.68)
Primary filer is male	−787.27	174.30	−1,272.49***	−771.78**
	(568.44)	(127.17)	(492.40)	(373.89)
Individual controls	Yes	Yes	Yes	Yes
Zip code controls	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes
R^2	0.086	0.099	0.064	0.067
N	37,054	37,054	55,815	55,815
N, weighted	507,819,121	507,819,121	412,673,931	412,673,931

Note: This table reports the results of a regression of audit adjustments to taxable income on an indicator for the use of a paid preparer and a set of control variables. The IV models instrument for preparer use using the fraction of taxpayers in the filer's zip code using paid preparers, the fraction of those in the filer's workplace using paid preparers, the fraction of filers who use a VITA preparer in the filer's zip code, the EITC claim rate in the filer's zip code, and the rate of e-filing in the filer's zip code — all interacted with male/female indicators (Column 1) or interacted with age and age squared (Column 3). Demographic controls include an indicator for dependents claimed, whether the primary filer is male, filing status, age, and age squared. Zip code–level controls include the log of population, the operational audit rate, tax-preparer market concentration, and average AGI. Schedule C, Schedule D, Schedule E, Earned Income Tax Credit, and Itemizer represent indicator variables for the presence of these forms on the taxpayer's return, EITC claim status, and itemization of deductions. Standard errors clustered at the zip code level are reported in parentheses below the point estimates. *N* denotes the number of observations. Asterisks denote significance at the 1% (***) and 5% (**) levels. All dollar values are in 2012$.

single male and single female filers, the magnitudes are more than twice as large for men as for women. A statistical test of the difference in coefficients on men's and women's interactions with paid preparer use finds that they are statistically different at typical confidence levels.[26] When measured as a percentage of mean

[26] The X^2 test statistic on the hypothesis that the coefficients on men's and women's interactions with paid preparer use are the same is 6.84, which corresponds to a p-value of 0.0089, meaning one can reject the null that these coefficients are equal with greater than 99 percent confidence.

taxable income for males, the increase in audit adjustments from using a paid preparer is about 25 percent of mean income, whereas for females it is 13 percent. These results are consistent with past studies that find women to be more conscientious and less prone to corruption than men (Eagly and Crowley, 1986; Eckel and Grossman, 1998; Dollar, Fisman, and Gatti, 2001) as well as evidence that men tend to engage in more tax evasion (Torgler and Valev, 2010).[27]

Next, we turn to heterogeneity in the effects of paid preparers by the age of the filer. To do this, we estimate a version of Equation (2) where we include terms that interact the filer's age with paid preparer usage.[28] In this case, we restrict our analysis to married filers and use the age of the primary filer. Table 7, Columns 3 and 4 report the results. We find a positive coefficient on age and a negative on age squared for both taxable income and total taxes, although both are statistically indistinguishable from zero owing to imprecise point estimates.

Finally, Figure 1 shows the effects of tax preparers on audit adjustments to taxable income of tax filers with different income levels. We estimate Equation (2) with interactions of paid preparer use with AGI category indicator variables. Based on their postaudit AGI, filers are grouped into one of six categories, from which we obtain two important results. First, tax preparers increase the size of audit adjustments to taxable income for taxpayers of all income groups with AGI greater than \$35,000.[29] This is consistent with the theory that the goal of paid preparers in general is to minimize taxes owed, regardless of the client's income. Second, the amount by which they understate both the taxable income and the total tax liability is generally increasing in income.[30] The exception to this is that we find preparer use decreases audit adjustments for those with incomes between \$0 and \$15,000. However, this could be reflective of changes in reporting to maximize the EITC or other benefits available to low-income households. Filers with incomes below \$0 are often wealthy households more similar to those in the highest AGI bin, and there is a large effect of paid preparers on audit adjustments to taxable income for this group, as there is for the highest AGI group. Note that the OLS results, also presented in Figure 1, show the same pattern but smaller point estimates, estimated with higher precision.

If we consider the increase in adjustments on returns prepared by professionals as a fraction of taxable income, we can get a better sense of the importance of preparer aggressiveness to a taxpayer's taxable income. For those with AGI between \$15,000 and \$35,000, adjustments are about 4 percent of taxable income, whereas they are about 15 percent of taxable income for those with AGI greater than \$150,000.

27 Note that the coefficient on the filers being a male is negative, suggesting that males have smaller audit adjustments on self-prepared returns. But the interaction term suggests that males using a paid preparer have larger audit adjustments than women using preparers.

28 In the first stage of these regressions, we use interactions of our peer-effects measure (the fraction of filers in the five-digit zip using preparers) with age and its square.

29 The point estimate is positive for those with AGI of \$15,000–\$35,000 but not statistically different from zero.

30 Figure 1 shows only our results for taxable-income adjustments, but a table with estimated coefficients for both taxable income and total tax is available in Appendix.

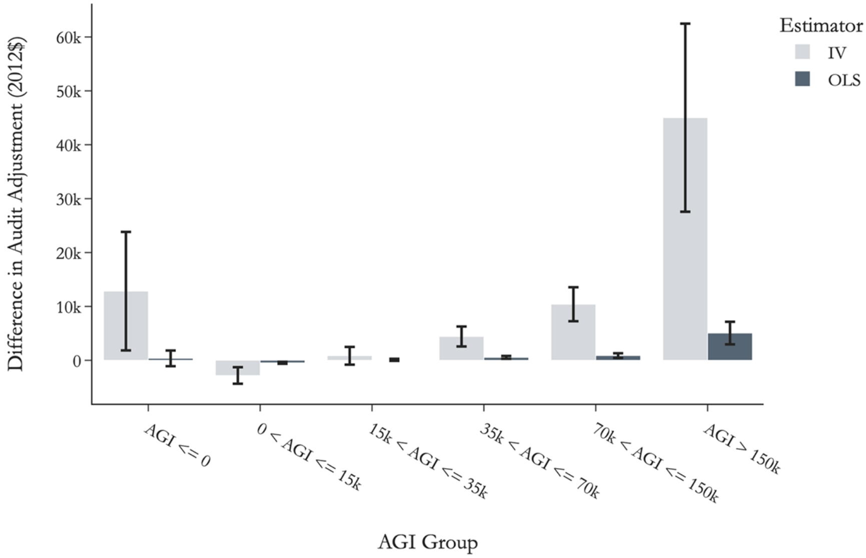

Figure 1. Differences in audit adjustments to taxable income for returns filed by paid preparers, by AGI group. The bars in this figure represent point estimates and 95 percent confidence intervals from the interaction of AGI groups with an indicator for paid preparer use. Results are from regressions of audit adjustments to taxable income on an indicator for the use of a paid preparer and a set of control variables. The IV model instruments for preparer use using the fraction of taxpayers in the filer's zip code using paid preparers, the fraction of those in the filer's workplace using paid preparers, the fraction of filers who use a VITA preparer in the filer's zip code, the EITC claim rate in the filer's zip code, and the rate of e-filing in the filer's zip code — all interacted with AGI categories. Demographic controls include an indicator for dependents claimed, whether the primary filer is male, filing status, age, and age squared. Zip code–level controls include the log of population, the operational audit rate, tax-preparer market concentration, and average AGI. Schedule C, Schedule D, and Schedule E are indicator variables representing the presence of these forms on the taxpayer's return. Indicator variables for Earned Income Tax Credit represent EITC claim status and whether the taxpayer itemizes deductions. Full results from these regressions are presented in Appendix A.

In summary, we find that the amount of additional noncompliance found among returns prepared by professional preparers is related to taxpayer characteristics. In particular, male taxpayers and taxpayers with higher income show larger audit adjustments than women or low-income filers when using paid preparers. We take this as evidence that at least some of the noncompliance amount paid to preparers is demand-driven.

E. Is Noncompliance Supply-Driven?

If the reduction in compliance by paid preparers is driven by characteristics on the supply side, then we should find that certain types of preparers underreport their clients' tax liability more. Here we consider two characteristics of paid preparers: their professional credentials and the competitiveness of their local market. Erard (1993) uses data from the 1979 TCMP to find that paid preparers who are CPAs or lawyers increase noncompliance rates by about 4.5 times what would be found on self-prepared returns. He finds smaller effects, an increase in noncompliance of about 15 percent, for other types of preparers. Figure 2 presents regression results from estimating a version of Equation (2) on audit adjustments to taxable income, with indicator variables for the type of preparer used (again with self-prepared returns as the excluded comparison group). Our instruments in the IV model estimates include our set of five instruments from our baseline model interacted with the preparer type the filer uses.[31] Our estimates show the largest point estimates on attorneys, which is qualitatively consistent with the results in Erard (1993), despite a gap of three decades. However, this estimate is very imprecise because attorneys prepare only about 0.27 percent of returns, and they likely are preparing returns for higher-income taxpayers, which, as we saw in Figure 1, displayed larger effects of preparers on audit adjustments. We have more precision in our estimates of the role of CPAs, enrolled agents, and other preparers. Audit adjustments to taxable income for returns filed with CPAs have adjustments of about \$360 higher than on self-prepared returns, but this estimate is not statistically different from zero. Interestingly, paid preparers working for large, national tax-preparation firms show essentially the same difference as CPAs in their audit adjustments relative to self-prepared returns, but with more precision we can distinguish this estimate from zero (although not from that of CPAs). Enrolled agents and other, unclassified types of preparers show the larger point estimates, with differences of more than \$800 relative to self-prepared returns.

Next, we consider market competition and concentration in the tax-preparation industry. To do this, we put each zip code into a quintile based on its tax-preparer HHI and interact the HHI quintile with the use of a preparer. We instrument for the HHI*preparer to use interaction effects by interacting each of our five IVs noted in Equation (1) with each HHI quintile. The coefficients on these interactions tell us how much larger or smaller audit adjustments are for those using paid preparers for each quintile of preparer market concentration. Our findings are presented in Figure 3. Economic theory would predict that in more competitive markets, tax preparers may compete over finding the lowest tax liability for their clients, which may incentivize them to push the boundaries of what is legal or appropriate for filers to claim. OLS estimates are consistent with this and suggest that adjustments to professionally prepared returns are largest in the most competitive markets. In these models, adjustments to taxable income are more than twice as large in the bottom quintile of HHI (least concentration) as they are in the top quintile (most concentration).

[31] Note that we are not able to observe the credentials of professional preparers in the population files over the full sample period and therefore do not use preparer-type specific usage rates at the zip code level for IVs.

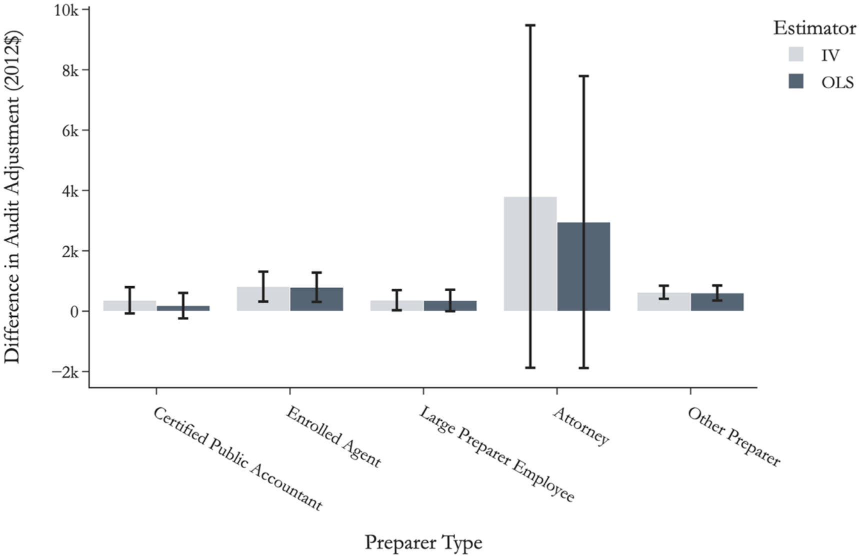

Figure 2. Differences in audit adjustments to taxable income for returns filed by paid preparers, by preparer type. The bars in this figure represent point estimates and 95 percent confidence intervals from the interaction indicator variables for the use of different types of paid preparers. Results are from regressions of audit adjustments to taxable income on an indicator for the use of a paid preparer and a set of control variables. The IV models instrument for preparer use using the fraction of taxpayers in the filer's zip code using paid preparers, the fraction of those in the filer's workplace using paid preparers, the fraction of filers who use a VITA preparer in the filer's zip code, the EITC claim rate in the filer's zip code, and the rate of e-filing in the filer's zip code — all interacted with preparer type. Demographic controls include an indicator for dependents claimed, whether the primary filer is male, filing status, age, and age squared. Zip code–level controls include the log of population, the operational audit rate, tax-preparer market concentration, and average AGI. Schedule C, Schedule D, and Schedule E are indicator variables representing the presence of these forms on the taxpayer's return. Indicator variables for Earned Income Tax Credit represent EITC claim status and whether the taxpayer itemizes deductions. Full results from these regressions are presented in Appendix A.

In contrast, IV estimates show no pattern between market concentration and the relationship between preparer use and audit adjustments.

VI. DISCUSSION AND LIMITATIONS

There are cases of taxpayers employing paid preparers in which the preparers do not sign off on the return. Such preparers are often termed "ghost preparers."[32] Ghost preparation is most common among low-income filers and the elderly (IRS 2020). If ghost preparation were entirely random across the population, the effect would attenuate our results due to the mismeasurement of who uses a preparer, which

[32] See Tolan (2012) for a summary of issues related to ghost preparation.

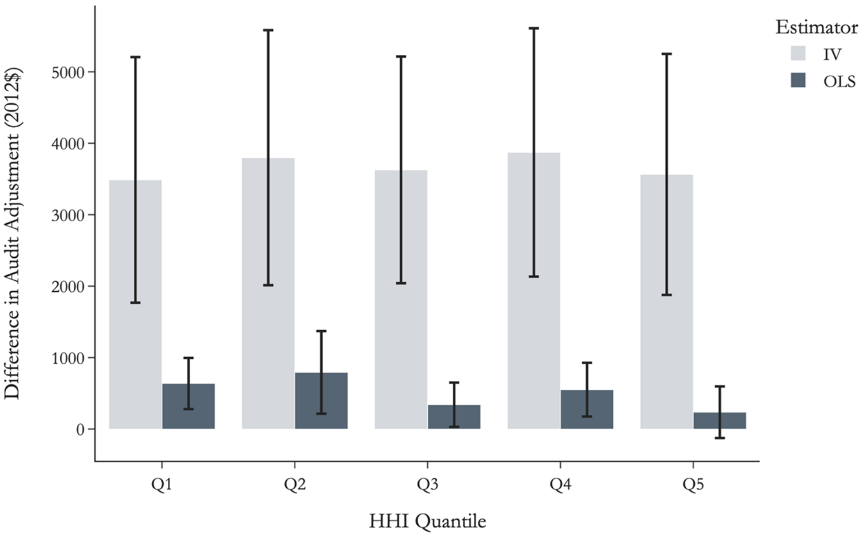

Figure 3. Differences in audit adjustments to taxable income for returns filed by paid preparers, by preparer market HHI. The bars in this figure represent point estimates and 95 percent confidence intervals from the interaction indicator variables for the use of different types of paid preparers. Results are from a regression of audit adjustments to taxable income on an indicator for the use of a paid preparer and a set of control variables. The IV models instrument for preparer use using the fraction of taxpayers in the filer's zip code using paid preparers, the fraction of those in the filer's workplace using paid preparers, the fraction of filers who use a VITA preparer in the filer's zip code, the EITC claim rate in the filer's zip code, and the rate of e-filing in the filer's zip code — all interacted with HHI quintile. Demographic controls include an indicator for dependents claimed, whether the primary filer is male, filing status, age, and age squared. Zip code–level controls include the log of population, the operational audit rate, tax-preparer market concentration, and average AGI. Schedule C, Schedule D, and Schedule E are indicator variables representing the presence of these forms on the taxpayer's return. Indicator variables for Earned Income Tax Credit represent EITC claim status and whether the taxpayer itemizes deductions. Full results from these regressions are presented in Appendix A.

would bias our measured effect of preparers toward zero. However, because ghost preparation is correlated with low-income and elderly filers who are often taken advantage of via ghost preparers, we cannot be sure of the direction of the potential bias from mismeasurement. On the one hand, we find that tax preparers serving low-income filers have smaller adjustments upon audit than self-preparer returns (see Figure 2). Thus, misclassifying the low-income returns done by ghost preparers as self-prepared returns would tend to bias upward the effects of preparers on audit adjustments. On the other hand, the fact that ghost preparers do not follow the rules and sign off on a return and that they are often taking advantage of others perhaps suggests they are more aggressive than the typical preparer in what they report, which would bias our estimated effects of preparers downward if we mistakenly attribute the ghost-prepared returns as self-prepared.

One may still be concerned about whether the exclusion restriction holds for our IV. The above analysis implements a number of strategies to reduce such a concern, including estimating fixed-effects models that control for time-invariant differences in compliance behavior across four-digit zip codes and showing the results are robust across several instruments.[33] Despite this, we acknowledge that our set of instruments, as in any IV approach, is still open to criticism, and it is worth discussing how the results might change if the exclusion restriction is violated.

Given our set of controls for compliance norms, such as zip code fixed effects and the operational audit rate in zip codes, perhaps the most compelling story that would entail a violation of the exclusion restriction of our peer-effect instruments is if peer effects indeed not only affect the cost of using one form of preparation over another but also affect the rate of noncompliance. Given the set of controls included, for this to be the case, it would have to be that the effect that peers have on the costs of evasion would be time-varying, not well proxied for by operational audit intensity, and vary between self-prepared and paid-prepared returns. In such a scenario, there would be a bias in our estimate of the effect of preparers on compliance. Thus, let us suppose that if peers use preparers, they not only lower the costs of using that method of preparation for a taxpayer but also share information about how to avoid more taxes when using a preparer. In this case, our estimates of the role of preparers on tax compliance would be biased upward, because we would be attributing the total role of peer effects, including the introduction to new tax-avoidance strategies, onto the coefficient on preparer use in our second stage.

Another possible story is that the information sharing among peers centers on tax-avoidance strategies, but that these strategies are only used on self-prepared returns, perhaps because professional preparers do not take the advice of their clients on methods of tax avoidance. In this case, the fraction of those who use preparers, which is the inverse of the fraction of self-preparing, will be negatively correlated with amount of peer sharing of tax-avoidance strategies for those who self-prepare. Under such a scenario, our point estimates on the role of paid preparers in tax compliance would be biased toward zero because an instrument, the fraction of filers using paid preparers, would be negatively correlated with the amount of tax avoidance on self-prepared returns.

Which of these scenarios is more likely is not something we can directly address, because they involve unobservable behaviors of taxpayers. However, Wakolbinger and Haiger (2009) provide evidence from a laboratory experiment showing that participants do respond to peer advice that lowers tax compliance when information is self-reported. This does provide suggestive evidence that peer effects may play a role in tax compliance in the field, but the empirical design of this research does not give a sense of whether this is more likely among those self-preparing or those using tax professionals to prepare their returns (they only consider self-preparation in the context of the experiment).

[33] These results are found in Table A5.

Another piece of suggestive evidence of the likely direction of bias if our exclusion restriction fails would be the comparison of coefficients on preparer use between our IV and OLS models. The OLS estimates are considerably smaller than the IV estimates in almost every instance. For example, in the IV models in Table 3, we find that a paid preparer increases the adjustment to taxable income by $3,902, whereas in the OLS model the same parameter estimate is $884. As we explain above, if the excluded instrument for preparer use (e.g., zip code preparer usage rates) is unrelated to compliance decisions except through the choice of using a preparer or not, then the downward bias in the OLS estimate represents the positive selection of taxpayers into preparer use. That is, taxpayers who select into preparer use are more likely to be more compliant (all else equal) than those who self-prepare their returns. However, if the exclusion restriction fails and if the excluded peer-effects instrument is related to compliance rates through another channel, such as learning about peers' strategies to avoid taxes, then the larger coefficients on the IV estimates could have resulted because they are biased upward.

VII. CONCLUSION

Despite the rise of tax-preparation software, human paid preparers are involved in the preparation of about 60 percent of all individual income tax returns. In this study, we find that these professional tax preparers are responsible for a large share of tax noncompliance by their clients. On average, they increase their clients' tax underreporting by about 87 percent compared with tax filers without their help. In terms of tax dollars, preparers help clients evade about $518 per tax return that they prepare. With about 60 percent of taxpayers using preparation services, this estimate implies a federal revenue loss of tens of billions of dollars each year due to tax preparers.

Further evidence shows that this is likely driven by incentives in the tax-preparation industry. In comparison, volunteer third-party preparers do not exhibit the same behavior as paid preparers and have audit adjustments that are not significantly different from self-prepared returns. Furthermore, the income and deduction sources from which most of the differences in adjustments stem (rental income, pass-through business income, charitable contributions, work expenses) are areas with little third-party documentation, suggesting that paid preparers may be exploiting areas where the IRS lacks readily available information for targeting their clients' returns.

In addition, we find that CPAs have relatively small adjustments to their filers' returns, whereas enrolled agents tend to have larger adjustments. Our results suggest that attorneys may be particularly aggressive, but we have little precision to say this with any degree of certainty. It also appears that the structure of the tax-preparation industry may play a role in the behavior of tax preparers.

However, taxpayer characteristics apparently also play a large role in noncompliance when using a tax preparer. In particular, the aggressiveness of tax preparers' reporting increases when they work with clients who are male and have higher income. We note that males are also found to engage in more illicit activities in other contexts.

Despite these findings, open questions about tax preparation remain. Although our analysis measures the effect of tax preparation as it is currently practiced, and our IV estimates represent estimates of the effects of preparers on taxpayers at the margin of choosing a preparer, it does not examine the implications of extending preparation services to the entire population of taxpayers. In addition, in this paper we examine the impact of using a tax preparer on noncompliance on that year's tax return. We leave it to future research to examine whether there is a longer-term impact of tax preparation on subsequent years' tax reporting.

Nevertheless, our findings open questions not only about tax preparers but also about other fields where professionals provide assistance that could be used to either comply with or better evade legal or ethical concerns.

ACKNOWLEDGMENTS

We thank Jim Alm, Vicki Perri, Nathan Seegert, Caroline Weber, John Guyton, and participants at the National Tax Association's meetings, the Tax Administration Research Center Workshop on Tax Audits Evaluation, the Utah Tax Invitational conference, and the Georgetown Tax Law and Public Finance Workshop for helpful comments. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the US Department of the Treasury or the Office of Tax Analysis.

DISCLOSURES

Jason DeBacker, Bradley Heim, and Anh Tran have no conflicts of interest related to this manuscript. This research was conducted while Alexander Yuskavage was an employee at the US Department of the Treasury. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors and do not necessarily reflect the views or the official positions of the US Department of the Treasury. Any taxpayer data used in this research were kept in a secured IRS data repository, and all results have been reviewed to ensure that no confidential information is disclosed.

REFERENCES

Allingham, Michael G., and Agnar Sandmo, 1972. "Income Tax Evasion: A Theoretical Analysis." *Journal of Public Economics* 1 (3–4), 323–338.

Angrist, Joshua, Victor Lavy, and Analia Schlosser, 2010. "Multiple Experiments for the Causal Link between the Quantity and Quality of Children." *Journal of Labor Economics* 28 (4), 773–824.

Batta, George, Andrew Finley, and Joshua Rosett, 2019. "The Effect of Paid Preparer Competition on Individual Tax Avoidance." Working paper, University of Hawaii.

Battaglini, Marco, Luigi Guiso, Chiara Lacava, and Eleonora Patacchini, 2019. "Tax Professionals: Tax-Evasion Facilitators or Information Hubs?" NBER Working Paper No. 25745. National Bureau of Economic Research, Cambridge, MA.

Benzarti, Youssef, 2020. "Estimating the Costs of Filing Tax Returns and the Potential Savings from Policies Aimed at Reducing These Costs." *Tax Policy and the Economy* 35, 55–85.

Bobek, D. D., R. W. Roberts, and J. T. Sweeney, 2007. "The Social Norms of Tax Compliance: Evidence from Australia, Singapore, and the United States." *Journal of Business Ethics* 74, 49–64.

Boning, William C., John Guyton, Ronald H. Hodge, Joel Slemrod, and Ugo Troiano, 2020. "Heard It through the Grapevine: Direct and Network Effects of a Tax Enforcement Field Experiment." *Journal of Public Economics* 190, 104261.

Dollar, David, Raymond Fisman, and Roberta Gatti, 2001. "Are Women Really the Fairer Sex? Corruption and Women in Government." *Journal of Economic Behavior and Organization* 46, 423–429.

Doran, Michael, 2009. "Tax Penalties and Tax Compliance." *Harvard Journal on Legislation* 46, 111–161.

Eagly, A. H., and M. Crowley, 1986. "Gender and Helping Behavior: A Meta-Analytic Review of the Social Psychological Literature." *Psychological Bulletin* 100, 283–308.

Eckel, Catherine C., and Philip J. Grossman, 1998. "Are Women Less Selfish Than Men? Evidence from Dictator Experiments." *Economic Journal* 108, 726–735.

Erard, Brian, 1993. "Taxation with Representation: An Analysis of the Role of Tax Practitioners in Tax Compliance." *Journal of Public Economics* 52 (2), 163–197.

Erard, Brian, 1997. "Self-Selection with Measurement Errors: A Microeconometric Analysis of the Decision to Seek Tax Assistance and Its Implications for Tax Compliance." *Journal of Econometrics* 81 (2), 319–356.

Gunter, Samara R., 2019. "Your Biggest Refund, Guaranteed? Internet Access, Tax Filing Method, and Reported Tax Liability." *International Tax and Public Finance* 26 (3), 536–570.

Hansen, Victoria J., and Richard A. White, 2012. "An Investigation of the Impact of Preparer Penalty Provisions on Tax Preparer Aggressiveness." *Journal of the American Taxation Association* 34 (1), 137–165.

Hite, Peggy A., and John Hasseldine, 2003. "Tax Practitioner Credentials and the Incidence of IRS Audit Adjustments." *Accounting Horizons* 17 (1), 1–14.

Internal Revenue Service, 2019. "Federal Tax Compliance Research: Tax Gap Estimates for Tax Years 2011–2013." https://www.irs.gov/pub/irs-prior/p1415--2019.pdf.

Internal Revenue Service, 2020. "IRS: Don't Be Victim to 'Ghost' Tax Return Preparers." https://www.irs.gov/newsroom/irs-dont-be-victim-to-ghost-tax-return-preparers.

Internal Revenue Service, 2021. "2021 Internal Revenue Service Data Book." https://www.irs.gov/pub/irs-prior/p55b--2022.pdf.

Kelchtermans, Stijn, Daniel Neicu, and Peter Teirlinck, 2020. “The Role of Peer Effects in Firms’ Usage of R&D Tax Exemptions.” *Journal of Business Research* 108, 74–91.

Kittl, Maximilian, 2015. “Does Professional Tax Preparation Matter? Empirical Evidence from Germany.” *Journal of Business Economics* 85 (3), 231–262.

Klassen, Ken J., Petro Lisowsky, and Devan Mescall, 2016. “The Role of Auditors, Non-Auditors, and Internal Tax Departments in Corporate Tax Aggressiveness.” *Accounting Review* 91 (1), 179–205.

Klepper, Steven, Mark Mazur, and Daniel Nagin, 1991. “Expert Intermediaries and Legal Compliance: The Case of Tax Preparers.” *Journal of Law and Economics* 34 (1), 205–229.

Klepper, Steven, and Daniel Nagin, 1989. “The Anatomy of Tax Evasion.” *Journal of Law, Economics, and Organization* 5 (1), 1–24.

Kopczuk, Wojciech, and Cristian Pop-Eleches, 2007. “Electronic Filing, Tax Preparers and Participation in the Earned Income Tax Credit.” *Journal of Public Economics* 91 (7–8), 1351–1367.

Long, James E., and Steven B. Caudill, 1987. “The Usage and Benefits of Paid Tax Return Preparation.” *National Tax Journal* 40 (1), 35–46.

Noll, Daniel, Colleen Dawes, and Varun Rai, 2014. “Solar Community Organizations and Active Peer Effects in the Adoption of Residential PV.” *Energy Policy* 67, 330–343.

Rosenthal, Leigh, Bonnie Brown, Julia L. Higgs, and Timothy J. Rupert, 2023. “Tax Software versus Paid Preparers: Motivations and Predictors for the Mode of Tax Preparation Assistance.” *Accounting Horizons* 37 (1), 173–191.

Ross, Justin M., Coady Wing, and Denvil Duncan, 2022. “The Effect of State Occupational Licensing of Paid Tax Preparation in Tax Professional Services.” Working paper. Indiana University.

Slemrod, Joel, and Nikki Sorum, 1984. “The Compliance Cost of the U.S. Individual Income Tax System.” *National Tax Journal* 37 (4), 461–474.

Solon, Gary, Steven J. Haider, and Jeffrey M. Wooldridge, 2015. “What Are We Weighting For?” *Journal of Human Resources* 50 (2), 301–316.

Tolan, Patrick E., 2012. “It’s about Time: Registration and Regulation Will Boost Competence and Accountability of Paid Tax Preparers.” *Virginia Tax Review* 31 (3), 471–544.

Torgler, Benno, and Neven T. Valev, 2010. “Gender and Public Attitudes toward Corruption and Tax Evasion.” *Contemporary Economic Policy* 28 (4), 554–568.

Wakolbinger, Florian, and Stefan Haiger, 2009. “Peer Advice in a Tax-Evasion Experiment.” *Economics Bulletin* 29 (3), 1653–1669.

Weinstein, Paul, Jr., and Bethany Patten, 2016. “The Price of Paying Taxes II: How Paid Tax Preparer Fees are Diminishing the Earned Income Tax Credit (EITC).” Memo. Progressive Policy Institute, Washington, DC.

Zwick, Eric, 2021. “The Costs of Corporate Tax Complexity.” *American Economic Journal: Economic Policy* (2), 467–500.