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An Uneven Impact of Emerging Technologies on Taxpayers With Various Income Levels Audited by the IRS: Empirical Evidence From an AI Technology Application and Regression Models

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This study aims to investigate the influence of emerging technology adoption on tax compliance, encompassing both the Internal Revenue Service's (IRS) compliance audits and taxpayers' compliance performance (collectively, tax compliance). We employed the Gradient Descent optimization algorithm, an artificial intelligence (AI) technology application, to scrutinize the connection between the quality of US tax filings and the development of emerging technology, among other contributing factors. Additionally, we utilized multiple linear regression to evaluate the relationships between dependent variables, specifically IRS audit rates and the no-change rate at different income levels,[1] and several independent variables, including a proxy for emerging technology in the form of tax software. Our findings reveal that while emerging technology significantly impacts tax compliance within the IRS and taxpayers' performance, its effects vary across income groups. Notably, emerging technology seems to confer greater advantages to higher-income individuals compared to their lower-income counterparts. These study results hold considerable policy implications for government decision-makers in promoting the adoption of emerging technology among lower-income taxpayers.

Keywords: IRS Audit, taxpayer compliance, emerging technology, artificial intelligence tax software, income levels

Introduction and Literature Review

The accounting profession has undergone a rapid transformation in recent years, with emerging technology playing a pivotal role in enhancing productivity. Modern accountants, no longer burdened by task-oriented projects, must develop new skills in informatics knowledge, critical thinking, and innovative analysis. Recognizing this trend and preparing for the challenges it presents is now a top priority for accounting professionals.

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[1] Audit rates are defined as IRS compliance audits that are divided by the total number of returns filed for that tax year, and no-change rates are defined as audits that are closed with no changes to taxes owed, divided by the total number of audits closed in that year (GAO, 2022). Both the audit rate and no-change rates are for individual nonfarm business taxpayer groups. In most cases, these audits are conducted in person by revenue agents, tax compliance officers, tax examiners, and revenue officer examiners (See IRS Data Book Table 17b). The change in no-change rates reflects taxpayers' compliance performance discussed in the body of this article.

It is widely believed that four or five major emerging technology areas are poised to reshape the accounting landscape: artificial intelligence and robotics, cloud computing, mobile accounting, and innovations in tax software (UWorld Roger CPA Review, 2023). This study specifically focuses on one of these areas: the impact of tax software on tax compliance.

Introduction

According to a recent GAO report (GAO, 2022), audit rates decreased for all income levels from 2010 to 2019. On average, the audit rate for tax returns dropped from 0.9 percent to 0.25 percent. The GAO report also reveals a decreasing number of no-change rates. IRS officials attributed the decline in audit rates primarily to reduced staffing resulting from decreased funding, and they explained that the no-change rate has generally decreased because the IRS conducts fewer audits. However, other researchers believe that current tax software has improved accuracy while reducing margins of error and streamlining audits, making both the IRS and the taxpayer more efficient and effective (Pepe, 2022).

We acknowledge that the IRS's decision to audit a tax filing can be influenced by a shortage of IRS staff, potentially affecting the number of audit cases. However, while we agree that audit rates may be affected by IRS workforce capacity, measured by the number of IRS employees, we cannot disregard the fact that audit rates can also be influenced by actual audit needs. Reduced audit rates could still meet the needs if overall filing accuracy improved, meaning that filing errors, calculation errors, and reporting errors were significantly reduced. Furthermore, we believe that the no-change rate, measured by the number of audits closed with no changes to taxes owed over the total number of audits, is not solely influenced by the absolute number of total filings or total audits, as claimed by the IRS. Instead, this rate is more affected by the actual quality of filings selected for auditing by the IRS since these cases are typically double-checked by experienced accounting professionals. If errors have become relatively scarce due to the application of tax software, the no-change rate will decrease.

Based on our analysis of supply (IRS labor resources) and demand (audit needs), we include IRS employees and tax software as independent variables affecting audit rates and the no-change rate, which serve as the primary measures of tax compliance for both the IRS and taxpayers. Our analysis suggests that tax software embodies more features of emerging technologies in the accounting field than e-filing. Therefore, we have chosen it as a proxy for emerging technologies. Tax software not only includes an e-filing function that helps taxpayers reduce filing errors but also aids in reducing calculation errors and reporting errors. Our empirical examination seeks to determine whether the proxy for emerging technology affects audit rates and the no-change rate and whether its impact, in addition to the number of IRS employees, is statistically significant.

Literature Review

The exploration of emerging technologies' influence on accounting is a relatively recent topic. Numerous empirical studies have predominantly focused on the effects of implementing the e-filing system on taxpayers' compliance. Yılmaz and Coolidge (2013), in collaboration with the World Bank Group (2018), identified a relationship between e-filing and tax compliance costs. In his research paper, Chen (2010) delved into the impact of quality antecedents on taxpayer satisfaction with online tax-filing systems. Chen's findings highlighted that the implementation of e-filing systems can enhance taxpayers' compliance.

Purba et al. (2019) conducted a modeling exercise using Indonesia's data and established that a higher implementation of the e-filing system corresponds to increased taxpayer compliance. Purba found that the simultaneous application of the e-filing system and Internet understanding has a substantial effect on taxpayer compliance. Kumar and Sachan (2017) delved into the factors influencing citizens' intention to adopt e-filing in the Indian context. The study found that enhancing e-filing system services enhances taxpayers' compliance and increases their intent to use them. The World Bank Group conducted a study using data from surveys of businesses in developing countries to investigate the association between the use of specialized tax software and total tax compliance costs. The World Bank Group's regression analysis showed that tax software may reduce tax compliance costs while holding other variables constant, but the results were weak and mixed.

Very few empirical studies have analyzed the impact of emerging technologies on tax authorities or taxpayers' tax compliance. No previous studies have empirically examined the impact of tax software on tax compliance in the United States using the Gradient Descent algorithm.

Object, Data, and Methodology

The primary objective of this study is to conduct a critical analysis of the potential impact of emerging technology on both IRS and taxpayers' tax compliance. Additionally, we aim to investigate which income level(s) of taxpayers derive greater benefits from new technology in their tax filings and which income level(s) gain more advantages from the use of tax software.

Application of the Gradient Decent Algorithm in IRS Auditing Quality Analysis

To commence our analysis, we employ the Gradient Descent algorithm to examine the correlation between the quality of US tax filings and the development of emerging technology. In order to quantify the quality of US tax filings and the level of emerging technology development, we utilize the IRS's no-change rate as a proxy for tax filing quality and tax software sales volume as a proxy for the application of emerging technology in taxpayers' compliance. The fluctuation in no-change rates reflects taxpayers' compliance performance, whereas the sales volume of tax software represents the extent to which emerging technology is integrated into taxpayers' compliance.

Methodology and data. The general model specification is as follows:

$$y_{it} = \beta_1 + \sum_{j=2}^{k} \beta_j X_{jit} + \sum_{p=1}^{s} \gamma_p Z_{pi} + \epsilon_{it} \tag{1}$$

where i is an individual, t is the time period, j is for observed independent variables, and p is an unobserved independent variable. In our model, the dependent variable y is no-change rate, and the observed independent variables are tax software sales volume, and the number of IRS employees. Unobserved independent variables were assumed to be zero. ϵ is error term representing the margin of error, which provides an explanation for the difference between the theoretical value of the model and the actual observed results. Both the dependent variable and the observed independent variable are national data for 19 years from 2001 to 2019.[2] We use the log transformation for all variables so that the model coefficients can be easily interpreted. β_1, is constant term, and β_j, the coefficients of the independent variables. Here β_2 and β_3 are for government policy and new tech, respectively. The goal was to quantitively measure the impact of new tech on tax compliance quality.

In the model, the no-change rate data are extracted from the IRS Data Book (Table 17b). Tax software sales volume is obtained from the total revenue (in 10 billion) of the leading tax software company, Intuit [TurboTax]. Among tax preparation software providers (including Intuit TurboTax, TaxSlayer, and H&R Block), Intuit's

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[2]. This is the most recent available data for a consistent measurement.

TurboTax is the dominant player, commanding a 73 percent market share as of May 2021. Intuit's sales data are sourced from its reports submitted to the U.S. Securities and Exchange Commission (FORM 10-K). The number of IRS employees (in 100 thousand) is drawn from selected IRS Data Books, specifically focusing on IRS full-time equivalent positions. The data used in this study span from 2001 to 2019, ensuring consistent data availability.

Gradient Descent is considered to possess a crucial characteristic in the estimation of U.S. tax filing quality, which is susceptible to fluctuations over time due to various factors, including technological advancements, shifts in IRS auditing policies, and unexpected changes in taxpayer cooperation. When training with noisy data using Gradient Descent, numerous strategies can be employed to enhance the likelihood of converging towards a global optimum, one of which is increasing momentum. Momentum facilitates rapid updates in consistent directions, resulting in gradient updates effectively "skipping" over noisy segments.

Gradient Descent serves as a fundamental first-order optimization algorithm widely employed in machine learning and deep learning for model training. Its primary objective is to minimize a function, typically a loss function, to its minimum point by following the path of steepest descent, thereby achieving the most accurate estimation. The loss function we used in our model is the mean squared error cost (MSE) function:

$$MSE(\theta_0) = \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)} - y^{(i)}) \tag{2}$$

$$MSE(\theta_1) = \theta_1 - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)} - y^{(i)}) \quad x^i \tag{3}$$

Gradient Descent updates θ_0 *and* θ_1 simultaneously and repeats until convergence. The goal is to minimize this function as shown in Figure 1.

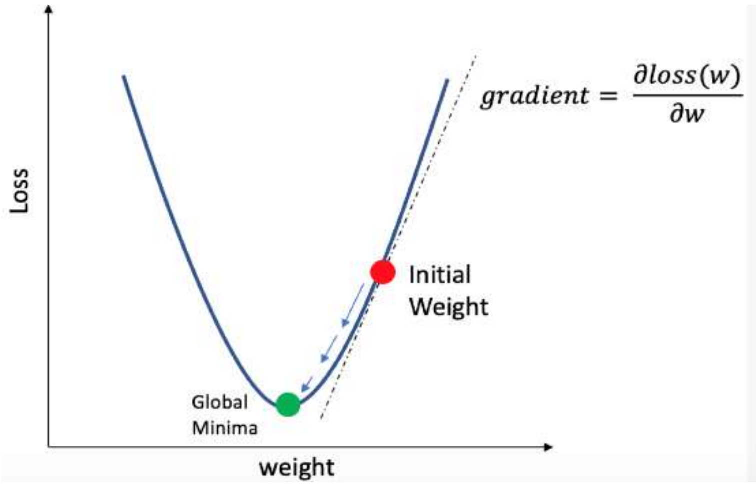

Figure 1. Loss vs. weights during gradient descent.

The y-axis shows the value of the loss function and weights. The graph displays the loss function and weights during Gradient Descent to minimize the loss function.

Gradient Descent iteratively refines the model parameters until reaching a state of convergence, where the parameters either cease to change or change at an exceedingly slow pace. This convergence state is typically identified when the disparity between the cost function values from two consecutive iterations becomes smaller than a specified, predefined value known as the convergence threshold.

It's worth noting that Gradient Descent operates as an iterative algorithm, and the number of iterations and the learning rate represent hyperparameters to be configured. In our model, we perform 1,000 iterations of Gradient Descent to guarantee the minimization of losses and the attainment of highly accurate estimates.

Gradient decent results and discussion. The Gradient Decent results are shown in Table 1.

Table 1

Metrics for Impact on US Tax Filing Quality

	Test score		Values
RMSE	0.16	β_1	0.80
MAE	0.12	β_2	-0.33[a]
R^2	0.86	β_3	1.31[b]

[a] When tax software sales volume increases by 1%, the no-change rate will decrease 0.8%. [b] When the number of IRS employees increases by 1%, US tax filing quality will increase by 1.31%.

Table 1 displays the root mean squared error (RMSE), mean absolute error (MAE), and *R*-squared values pertaining to our model.

RMSE stands as a commonly used metric to gauge the precision of a forecasting model, with a lower RMSE value signifying superior model performance. The test data's RMSE score of 0.16 reflects the average variance between actual and predicted values in the testing dataset. Since the testing dataset contains previously unobserved data, it serves as an assessment of the model's capacity to generalize to new, untrained data. A test score of 0.16 indicates that, on average, the model's predictions for the testing data differ by approximately 0.16 units from the actual values. Furthermore, the mean absolute error (MAE) quantifies the average deviation between predicted and actual values. With a test score of 0.12 MAE, it becomes apparent that the predicted values closely align with the actual values on average.

The *R*-squared value (R^2), also known as the coefficient of determination, quantifies the proportion of variance in the dependent variable that can be elucidated by the independent variables. The model's *R*-squared value for the test data stands at 0.86, indicating that the variations in the independent variables within the model can elucidate 86% of the fluctuations in qualification rates.

In this model, iteration = 1,000, Loss = 0.0102386 which reveals that the model underwent 1,000 iterations to optimize its parameters. The loss value of 0.0102386 denotes the final result of the loss function, which measures the dissimilarity between the model's predictions and the actual values. A lower loss value signifies a more accurate fit of the model to the data.

The actual and estimated values for no-change rates are presented in Figure 2.

The above application of Gradient Decent algorithm indicates that the relationship between tax software sales volume and the no-change rate in US tax filings is a compelling one. Our findings reveal that for every 1% increase in tax software sales, there is an associated 0.8% decrease in the no-change rate. This means that as more taxpayers utilize advanced software for their tax compliance, there is a concurrent improvement in the overall quality of tax filings. A lower no-change rate signifies a higher level of tax filing quality, indicating a reduction in errors and inaccuracies.

Similarly, the presence of IRS employees plays a pivotal role in enhancing the quality of tax filings. Our research indicates that for every 1% increase in the number of IRS employees, there is a substantial 1.31% improvement in US tax filing quality. This relationship underscores the importance of adequate IRS staffing in ensuring that tax compliance is accurate and efficient.

Taken together, these findings underscore the critical role of both emerging technology and the IRS workforce in shaping the quality of tax filings. To further enhance tax compliance and reduce errors, it is imperative for the government to actively encourage the adoption of advanced technology and sophisticated software within the US tax compliance system. Additionally, ensuring a sufficient number of IRS employees is essential to maintain the high quality of tax filings and to provide effective oversight. This not only benefits the government but also provides taxpayers with a smoother and more accurate tax filing experience, ultimately contributing to the overall efficiency and integrity of the tax system.

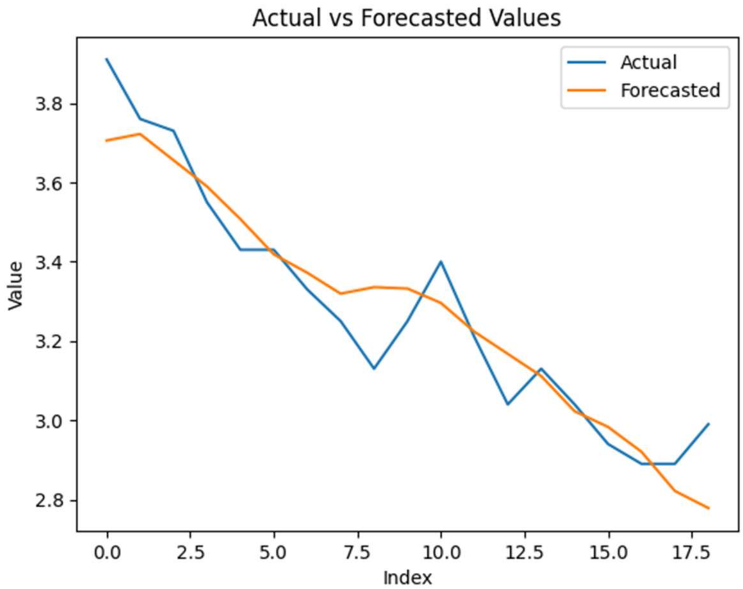

Figure 2. Actual and estimated values for the drop of no-change rates.
The model results show a relatively good fit between the forecasted and actual values for no change rate, demonstrating the model's ability to produce relatively accurate estimates.

Quantitative Analysis of Emerging Technology Impact on Taxpayers by Income Groups

In this section, the social impacts of new technology are examined: which will show which taxpayer income level(s) take more advantage of new technology in tax filings than others, and which taxpayer income level(s) benefit more from tax software than others.

Methodology and data. As per the objectives of the study, the null and alternative hypotheses framed are as follows:

H_0: There is no significant effect of emerging technology on IRS audit rates or no-change rates.

H_1: Emerging technology has a significant effect on IRS audit rates or no-change rates.

We use audit rates and no-change rate data at different income levels from the IRS Data Book (Table 17b). We use the total revenue (in 10 billion) of the tax software company Intuit [TurboTax] as a proxy for the tax software variable because among tax prep software (Intuit TurboTax, TaxSlayer, and H&R Block), Intuit's TurboTax is king, holding 73 percent of the market share as of May 2021. Intuit's sales data are from its reports to the U.S. Securities and Exchange Commission (FORM 10-K). The IRS employees number (in 100 thousand) is from selected IRS Data Books (IRS full-time equivalent position). This study is based on data from 2004 to 2019 for consistent data availability.

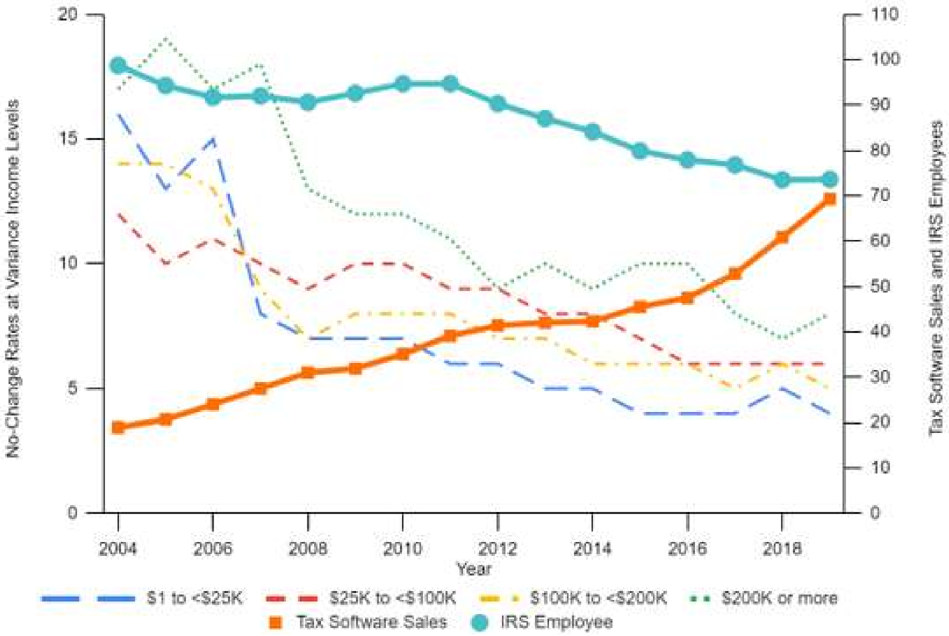

Figure 3. No-change rates at various income levels vs. tax software sales and IRS employees.

We attempted to determine the functional dependency between dependent and independent variables. We used the following multiple linear regression models (Model (I) and (II)) in our analysis:

$$\text{(I)} \quad \underline{AUDTR} = \alpha+\beta 1\text{TAXSFTW}+\beta 2\text{IRSEMPLY}+\epsilon \tag{I-1}$$

$$\underline{AUDTR} = \alpha + \beta(\text{either TAXSFTW or IRSEMPLY})+\epsilon \tag{I-2}$$

$$\text{(II)} \quad \underline{NOCHGR} = \alpha+\beta 1\text{TAXSFTW}+\beta 2\text{IRSEMPLY}+\epsilon \tag{II-1}$$

$$\underline{NOCHGR} = \alpha+\beta(\text{either TAXSFTW or IRSEMPLY})+\epsilon \tag{II-2}$$

The dependent variables are the audit rate (AUDTR) at different income levels for Model (I) or no-change rates (NOCHNGR) at different income levels for Model (II). Tax software sales (TAXSFTW) and number of IRS employees (IRSEMPLY) were taken as the independent variables in the model. β, $\beta 1$, and $\beta 2$ are the coefficients of the independent variables TAXSFTW and/or IRSEMPLY. The goal was to determine the mean expected value of the dependent variables ($\underline{AUDTRk}$ or $\underline{NOCHNGRk}$). The least-squares method is a form of mathematical regression analysis used to determine the line of the best fit for a set of data. Thus, we use this method to estimate the coefficients α, $\beta 1$, and $\beta 2$ for Equation (1) and α and β for Equation (2) with the aim of minimizing the sum of squared errors (SSE), as represented by the following expression:

$$SSE = \sum_{k=1}^{n}(\text{AUDTRk} - \underline{AUDTRk)^2} = \sum_{k=1}^{n} \text{AUDTRk} - \underline{(\alpha + \beta 1\text{TAXSFTW} + \beta 2\text{IRSEMPLY})^2} \quad \text{for (I)}$$

$$SSE = \sum_{k=1}^{n}(\text{NOCHNGRk} - \underline{NOCHGRk}^2 = \sum_{k=1}^{n} \text{AUDTRk} - \underline{(\alpha + \beta 1\text{TAXSFTW} + \beta 2\text{IRSEMPLY})^2} \quad \text{for (II)}$$

where AUDTRk or NOCHNGRk is the actual value of the dependent variable, estimated by the k-th respondent ($k = 1, \ldots n$); $\underline{AUDTRk}$ or $\underline{NOCHGRk}$ is the estimated value of the dependent variable for the k-th respondent ($k = 1, \ldots n$), and n is the total number of observations. The optimal mean value of the dependent variables is determined, given the assessed values of the dependent and independent variables for $\forall$k, $k = 1, \ldots$ n.

We used the coefficient of determination test (R^2) and the significant test of individual parameters (t statistic) to test our hypothesis. Our regression analysis is conducted in the following steps. First, we test two independent variable equations for each income level (Equation (1)). If we find that the values of the t statistic for all two individual parameters are significant and R^2 is significantly high, we will retain the equations. However, if only one variable's t statistic is significant with a high R^2, we remove the variable with an insignificant t statistic and re-run the regression with that significant independent variable (Equation (2)).

Multiple linear regression results and discussion. In this section, multiple linear regression models are used. In general, an R-squared (R^2) value greater than 0.6 and an individual t statistic greater than 2 (in absolute value) indicate that a model is worthy of our attention, although there are other factors to consider. For each income level in Model (I) and (II), we first run Equation (1), which includes two independent variables. If R^2 and t statistic values are higher than 0.6 and 2, respectively, we will consider that the model has a good fit. If not, we remove the independent variable with a t statistic lower than 2 and re-run the regression (Equation (2)).

We first examined the relationship between the no-change rate as a dependent variable and tax software sales (TAXSFTW) and IRS employees number (IRSEMPLY) as independent variables. From the regression results in Table 2, we observed a general pattern. That is, at lower income levels ranging from under \$25,000 to under \$100,000, the t statistic values of the tax software are all lower than 2, which means that the tax software's effects on no-change rates are not significant at these income levels. For example, at \$25,000 under \$100,000 income level, the tax software's t statistic is -1.742. Since -1.742's absolute value is less than 2, it is more likely that the tax software's effect on no-change rates is not significant at this income level. On the contrary, the IRS employees' number at this income level had a greater impact on no-change rates, and thus the IRS employees variable was kept while the tax software was removed in Equation (2). For example, the t statistic values for the IRS employees variable at an income level under \$25,000 were 2.181 and 4.973 for Equations (1) and (2), respectively.

There is a different trend for higher income levels. The impact of tax software on no-change rates is generally greater for those with lower income levels. For example, at an income level of \$100,000 under \$200,000, we first ran Equation (1) and found that R^2 was 0.70, and the t statistic was -2.667 for the tax software and -0.309 for IRS employees. We then removed the IRS employees variable with a low t statistic and re-ran the model with a tax software variable with a t statistic higher than the absolute value of 2. The results for the new model are satisfactory: R^2 is kept as high as 0.78, and the t statistic for the tax software is now -7.099. We saw a similar trend for an income level of \$200,000 or more. The t statistic values for tax software variables are -4.103 and -7.099 for Equations (1) and (2), respectively, and R^2 values are 0.801 and 0.782, respectively. Therefore, for these two higher income levels (\$100,000 under \$200,000 and \$200,000 or more), null hypotheses were rejected, and alternative hypotheses were accepted: emerging technology has a significant effect on no-change rates.

Table 2
Regression Results and Analysis of Dependent Variable: No-Change Rates

Income level	Equation*	Tax software			IRS employees			Model		Degree of freedom		
		Coef.	t stat	p value	Coef.	t stat	p value	R^2	Sig. F	Regre-ssion	Residual	Total
Under \$25,000	(1)	-0.389	-1.523	0.025	-0.085	2.181	0.644	0.645	0.001	2	13	15
	(2)				-0.224	4.973	0.000	0.638	0.001	1	14	15
\$25,000 under \$100,000	(1)	-0.044	-1.742	0.105	0.154	3.537	0.003	0.916	0.000	2	13	15
	(2)				0.222	10.999	0.000	0.896	0.000	1	14	15
\$100,000 under \$200,000	(1)	-0.199	-2.667	0.019	-0.039	-0.309	0.762	0.700	0.0004	2	13	15
	(2)	-0.244	-7.099	0.000				0.780	0.0000	1	14	15
\$200,000 or more	(1)	-0.322	-4.103	0.001	-0.148	-1.108	0.288	0.801	0.000	2	13	15
	(2)	-0.244	-7.099	0.000				0.782	0.000	1	14	15

* Equations (1) has two independent variables while Equation (2) has one independent variable.

Next, we examined the relationship between IRS audit rates (AUDTR) and tax software sales (TAXSFTW) and IRS employees' numbers (IRSEMPLY). The regression results are summarized in the following table:

Table 3

Regression Results and Analysis of Dependent Variable: Audit Rates

Income level	Equation*	Tax software			IRS employees			Model		Degree of freedom		
		Coef.	*t* stat	*p* value	Coef.	*t* stat	*p* value	R^2	Sig. *F*	Regre-ssion	Residual	Total
Under $25,000	(1)	-0.011	-2.230	0.044	0.008	1.00	0.334	0.804	0.000	2	13	15
	(2)	-0.015	-7.224	0.000				0.788	0.000	1	14	15
$25,000 under $100,000	(1)	0.060	1.932	0.075	0.107	2.005	0.066	0.240	0.168	2	13	15
	(2)				0.014	0.557	0.586	0.022	0.586	1	14	15
$100,000 under $200,000	(1)	0.083	1.466	0.166	0.186	2.017	0.077	0.237	0.172	2	13	15
	(2)				0.058	1.321	0.208	0.111	0.208	1	14	15
$200,000 or more	(1)**	0.090	3.302	0.006	0.171	3.675	0.003	0.510	0.010	2	13	15
	(2)**				0.032	1.234	0.238	0.098	0.238	1	14	15

** Equation (1) had high *t* statistic values for both tax software and IRS employees but a low R^2 value. Equation (2) does not improve R^2.

From Table 3, we can see that the *t* statistic values for IRS employees at various income levels are generally significantly high, except for the income level under $25,000, and the coefficients are positive for all income levels. This indicates that the drop in IRS audit rates in recent years may have had something to do with the drop in IRS employees numbers at most income levels. However, the R^2 values for these income levels, ranging from 0.022 to 0.510, are generally very low, indicating that a very small change in audit rates can be explained by IRS employees' change.

Regarding the effect of the tax software variable on IRS audit rates, we saw mixed results for Equation (1). The *t* statistic values for income levels of under $25,000 and $200,000 or more are -2.230 and 3.302, respectively, both above 2 in absolute values. Similarly, *t* statistic values for income levels $25,000 under $100,000 and $100,000 under $200,000 are 1.932, and 1.466, respectively, both below 2 in absolute values. Since the *t* statistic values are significantly high for the two income levels and are not significantly high for the other two income levels, the overall impact of tax software on the IRS audit rate is not conclusive.

Conclusion

The application of the Gradient Descent algorithm revealed that increasing tax software sales volume by 1% led to a corresponding 0.8% decrease in the no-change rate, indicating improved tax filing quality. Additionally, a 1% increase in the number of IRS employees resulted in a significant 1.31% enhancement in US tax filing quality. These findings underscore the substantial impact of both emerging technology and IRS workforce size on the quality of tax filings. To further improve tax compliance, it is crucial for the government to promote the adoption of advanced technology and sophisticated software in the tax system while ensuring an adequate number of IRS employees.

In addition, the Section of Quantitative Analysis of Emerging Technology Impact on Taxpayers by Income shows some interesting results.

Regarding no-change rates, their correlations with tax software are all negative and their correlations with IRS employees are all positive, while the correlations are generally high, ranging from -0.799 to -0.914 for the former and from 0.686 to 0.947 for the latter. The findings show that IRS employees and tax software impact audit rates, but the effect is minor. Comparatively, IRS employees and tax software generally have higher corrections with no-change rates than with audit rates.

In the realm of regression analysis, our investigation has unveiled a crucial insight into the impact of emerging technology, specifically the use of tax software, on tax compliance across various income levels. A noteworthy finding is that emerging technology exerts a significant influence on no-change rates for all income brackets exceeding $100,000. This underscores the pivotal role of technology in enhancing the quality of tax filings, leading to fewer discrepancies and errors in higher income segments. However, our analysis did not reveal a direct causal link between the reduction of IRS staffing and the fluctuations in audit rates and no-change rates. This suggests that IRS employee numbers alone do not comprehensively account for the dynamics in these aspects of tax compliance.

Therefore, it can be concluded that emerging technology has a more pronounced impact on no-change rates than on audit rates across income levels surpassing $100,000. In contrast, audit rates appear to be more closely associated with IRS employee numbers. This uneven impact of emerging technology across different income groups emphasizes that it predominantly benefits higher-income individuals.

These study results carry significant policy implications for government decision-makers. To foster equitable tax compliance and enhance the efficiency of tax systems, there is a need to promote the adoption of emerging technology, particularly among lower-income taxpayers. Balancing the distribution of technology's advantages across diverse income groups is vital.

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