**Big data analytics in IRS audit procedures and its effects on tax compliance:
A moderated mediation analysis**

ABSTRACT

Big data analytics could be a panacea for the IRS by enabling creation of taxpayer profiles to better capture noncompliance using artificial intelligence and machine learning, requiring less manpower. Privacy, fair information practices, and embedded biases are critiques of such practices, and little is known as to how taxpayers will respond. Deterrence theory suggests improvement in audit selection will increase compliance but excludes nonpecuniary factors of compliance, including taxpayers' perceptions of fairness. We test a moderated mediation model examining the role of procedural fairness on the relationship between audit procedures and tax compliance at varying levels of income traceability. We find that when income is more traceable, use of advanced technologies in audit selection increases taxpayer compliance by 16 percent with no effect on perceptions of fairness; when income is less traceable, use of advanced technologies has no effect on tax compliance, but decreases perceptions of fairness by 14 percent.

Keywords: big data analytics, taxpayer privacy, tax compliance, procedural tax fairness

I. INTRODUCTION

This study examines individual income tax compliance in response to changes in IRS audit selection procedures and most notably, their foray into the use of big data analytics. Recent articles have begun to shed light onto how the IRS is using these and other advanced technologies to detect tax evasion and more effectively target audits. A *Wall Street Journal* article warns "The machines are watching," in that the IRS is using machine learning and artificial intelligence to plot relationships among participants in business deals, create heat maps identifying concentrations of non-filers, and test which combinations of notices and contacts are most likely to procure taxpayer payment (Rubin 2020). The IRS collects both publicly-available data from social media sites such as Facebook, Twitter, and Instagram and holds contracts with data-mining firms to provide the agency with data necessary to functionalize these technologies (Rubin 2020, Houser and Sanders 2017).

However, the IRS' use of big data analytics and advanced technologies is not all that new. A 2009 IRS training document provides detailed tips to agents on how to conduct searches, locate taxpayer information, narrow and refine results, and use Adobe's Web capture feature to document relevant findings (Vijayan 2010). The training document describes a scenario where a man does stand-up comedy on the side and advertises his shows on his Facebook page; agents are then instructed to compare expected income from posted show dates to reported income on the man's tax return to identify possible under-reporting.

The use of big data to supplement traditional data collected for IRS audit selection has dual benefits – the opportunity to capture noncompliance on a broader scale and the ability to do so by use of artificial intelligence and machine learning, requiring fewer costly manpower hours. The predominant opposing concern pointed out by researchers is the privacy concern that may well arise as taxpayers become informed of just how much information the IRS is collecting on them. This paper provides experimental evidence to illustrate potential consequences of these decisions[1].

Traditionally, the IRS has used techniques such as checks of mathematical errors, document mismatching, and noncompliance. Beginning in 1962, the IRS began using computers to select tax returns for audit, and created the Taxpayer Compliance Measurement Program (TCMP) in 1964. The TCMP randomly selects about 50,000 returns every three years for a highly detailed audit. Results derived from the TCMP helped create a dataset of noncompliance from which evolved an automated program known as the discriminant function analysis (DIF), which calculates a probability of noncompliance for each tax return. In 2002, the IRS instituted the National Research Program (NRP) to replace the TCMP in order to gather data from random audits to assess voluntary tax compliance and provide data to improve the DIF audit selection. More recently, the IRS has used big data analytics to refine their audit selection. The primary difference between historical data gathering done by the IRS and their current strategies is the sourcing of the data; traditionally, the IRS used data from taxpayers and third party matching programs, whereas the IRS currently purchases big data from data brokers, the internet, and other governmental agencies (Houser and Sanders 2017). Other reports have indicated that the IRS supplements these strategies with artificial intelligence such as "spiders," or automated computer programs to review social media sites (Freeman 2019).

Big data analytics has been hailed as a remedy to the IRS' much-documented budget concerns. Adjusting for inflation, the IRS budget for 2019 is $11.3 billion less than in 2000, and headcount has declined by 38 percent since 2010 (Cohn 2019). Diminishing budget and

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[1] Approval from the Institutional Review Board (IRB) has been granted by the institution at which this experiment took place.

headcount directly result in a decrease in collected tax revenues. The use of big data analytics at the IRS was termed as "solving a big problem, problematically" (Harvard Business School 2018). Though these new technologies and datasets help the IRS to more efficiently collect revenue with a diminished workforce, the strategies have been criticized for their lack of notice to taxpayers, lack of transparency in the algorithms, and privacy concerns, with some going so far as to say that the IRS is breaking the laws with their data mining (Houser and Sanders 2017). Edward Zelinsky, Professor at Yale Law School, notes that "[these strategies are] well-known in the tax community, but not many people outside of it are aware of this big expansion of data and computer use [by the IRS]" (Satran 2013).

Furthermore, it is unknown at this point as to how taxpayers will react upon learning about the ways in which the IRS is developing detailed taxpayer profiles on which to run their audit selection procedures. Whereas traditional deterrence theory (Allingham and Sandmo 1972) suggests that probability of detection is a key motivating factor in tax compliance, the behavioral tax literature finds that voluntary tax compliance, or tax morale, is dependent on factors such as intrinsic motivation to pay, perceptions of tax fairness, and reciprocal altruism, in which taxpayer compliance is dependent on how the government itself uses tax revenue and therefore behaves in the interest of its citizens (Frey 1997).

As it relates to the context of audit selection, procedural fairness, sometimes called procedural justice, in this case would be valued in that it produced a fair allocation of audits across all taxpayers. Leventhal (1980) identifies six procedural justice rules to be satisfied for an allocative process to be considered fair; the three most relevant to this context include bias-suppression, ethicality, and consistency. Criticism of the IRS' use of data mining and advanced technologies has focused on issues such as lack of transparency in algorithms, lack of notice to taxpayers, privacy concerns, and the potential for prejudice in algorithms. Depending on the taxpayer and how they weigh the rules of procedural justice, these criticisms may violate the rules and create the perception of an unfair process. Other taxpayers might defer to the consistency rule in that more mechanistic, machine-determined audits lead to more even allocation of audits as compared to random selection.

This study experimentally examines individual taxpayer compliance in response to the IRS' use of big data analytics in audit selection procedures. Deterrence theory suggests that the improvement in audit selection will increase compliance, but does not recognize in its model the nonpecuniary factors of compliance, and specifically to this context, taxpayer perceptions of procedural fairness at the IRS. We test a moderated mediation model examining the mediating role of procedural fairness on the relationship between IRS audit selection procedures and tax compliance at varying levels of income traceability. We manipulate IRS audit selection procedures at two levels: basic technologies, including traditional audit selection procedures such as document matching, and advanced technologies, including the use of artificial intelligence and machine learning to analyze new sources of big data. We also manipulate the traceability of the contract income earned by the taxpayer at two levels: low traceability, where income was advertised through word of mouth, and high traceability, where income was advertised on various social media platforms.

We find that when income is more traceable, the IRS' use of advanced technologies is associated with a marginally significant 16 percent increase in tax compliance and no significant effect on perceptions of procedural fairness; when income is less traceable, the IRS' use of advanced technologies has no significant influence on tax compliance, but decreases perceptions of procedural tax fairness by a statistically significant 14 percent. Though an increase in tax compliance and tax collections is clearly the goal of the IRS' use of big data analytics and advanced technologies, the IRS should be aware of the unintended consequences of such procedures on tax morale.

This paper contributes to the literature in the following ways. It is the first study to our knowledge to address the IRS' use of big data analytics in its audit selection procedures and to provide empirical evidence on their effects on tax compliance. Further, this study examines the effects of taxpayer knowledge of these procedures on perceptions of procedural tax fairness. These findings ought to be of particular interest to the IRS given the strong relationship identified by prior research between procedural tax fairness and willingness to comply with tax policy. Given recent attention given to privacy concerns, particularly as it relates to information shared on social media sites, taxpayer knowledge of these procedures could elicit criticism. Second, this study builds upon the theoretical model linking procedural tax fairness and tax compliance by identifying additional predictors of procedural tax fairness in detection risk related to audit selection and detection risk related to income type. Farrar, Massey, Osecki, and Thorne (2020) note that the concept of fairness has limited use in the tax context, and this study uses this concept to identify the mediating effect of fairness between IRS audit selection procedures and tax compliance.

The remainder of this study is organized as follows. Section two reviews the literature and develops the hypotheses. Section three describes the methodology used to test these hypotheses. Section four presents the results, and section five concludes.

II. PRIOR RESEARCH AND HYPOTHESES DEVELOPMENT

This section develops hypotheses about the impact of two elements of detection risk, audit selection procedures and income traceability directly on procedural tax fairness and indirectly on tax compliance. Deterrence theory states that increased probability of detection directly increases compliance, and expected utility theory, upon which deterrence theory is based, suggests that detection is the predominant driver of compliance (Alm 2019). Extensive tax compliance literature has found, however, that nonpecuniary factors can cause compliance to deviate from expected levels as predicted by deterrence theory, specifically, when tax morale is low. We expect that while the IRS' use of big data analytics and artificial intelligence in its audit selection procedures will increase the probability of detection and therefore increase compliance, under certain circumstances, these methodologies will elicit a decrease in perception of procedural tax fairness such that the increased probability of detection does not influence compliance behaviors. These expectations are formally hypothesized below and in Figure 1.

Deterrence Predictors of Tax Compliance

First models predicting rates of individual income tax compliance were based upon the economics-of-crime model (Becker 1968) and utility maximization. Allingham and Sandmo (1972) provided such a model, suggesting that taxpayers choose between two strategies: declaration of actual income, and declaration of an amount less than actual income. The utility of either option is dependent on a jurisdiction's statutory tax rate and factors intended to deter avoidance – the probability of detection (i.e. audit rate) and the penalty rate on detected unreported income[2]. This model suggests that taxpayers calculate the expected utility of both strategies under this model and report their income accordingly. Most notably as it relates to this study, Allingham and Sandmo conclude that "an increase in the probability of detection will always lead to a larger income being declared, (p.330)" and more recent research has confirmed

[2] Though much of the behavioral tax literature documents a plethora of predictors of individual income tax avoidance beyond the deterrence factors identified by the Allingham and Sandmo (1972) model, Allingham and Sandmo also provide an expanded model to include nonpecuniary costs, broadly identified as the effect on one's reputation as a citizen of the community.

that "standard expected utility theory concludes that enforcement is the single key factor that motivates compliance" (Alm 2019).

Kirchler, Muehlbacher, Kastlunger, and Wahl (2010) provide a review of the literature which has empirically examined specific elements of the Allingham and Sandmo (1972) model. Ali, Cecil, and Knoblett (2001) analyze an IRS dataset and find that the compliance rate was higher when the audit rate was higher; this result was more pronounced for high-income earners. In addition, the relationship between audit rates and compliance has been studied extensively experimentally. Alm, Sanchez, and De Juan (1995) compare three audit rates (5%, 30%, 60%) and find that each audit rate increase was accompanied by an increase in compliance. Trivedi, Shehata, and Lynn (2003) and Trivedi, Shehata, and Mestelman (2004) compare a zero-audit rate with a 25% audit rate and similarly find that compliance rates were higher with the increased audit rate. Spicer and Thomas (1982) compare precise audit rates (denoted in percentages) with imprecise audit rates (denoted as low, medium, high) and find that increases in both types of audit rates are associated with increases in compliance. However, precise information was more impactful on compliance behavior as compared to imprecise information.

While this research concludes that audit rate is associated with compliance rates, more recent research has asserted that it is the *perceived* audit rates, or probability of detection, which influences behavior, rather than *actual* audit rates (Alm 2019). Prior literature has determined that taxpayers often misperceive actual audit rates in that they determine their probability of detection to be significantly higher than it actually is (Aitken and Bonneville 1980, Webley 1991, Kirchler 2007). The 'slippery slope framework' (Kirchler, Hoelzl, and Wahl 2008) includes (1) enforced tax compliance, (2) trust in authorities, and (3) power of authorities in its determinants of levels of voluntary tax compliance. Enforced tax compliance includes deterrence factors such as audit rates, and power of authorities extends this to include taxpayers' perceptions of the potential of tax officers to detect evasion and conduct an effective tax audit.

Nonpecuniary Predictors of Tax Compliance

Where deterrence factors provide a requisite baseline for understanding predictors of tax compliance, most recent literature has examined nonpecuniary predictors of tax compliance. This pivot has occurred because, simply, "the deterrence model predicts too much evasion (Frey 2003, p.387). Slemrod (2019) broadly categorizes nonpecuniary predictors of tax compliance into the following. The first category is taxpayers' civic duty or intrinsic motivation to contribute, and Frey (1997) warns that governments not overreach with deterrence strategies such that intrinsic motivation is overwhelmed by governmental enforcement. The second category is the tax enforcement system, and the third is taxpayers' attitudes toward authority. The fourth and final category is reciprocal altruism, in which Levi (1989) indicates that taxpayer compliance is dependent on how the government itself uses tax revenue and therefore behaves in the interest of its citizens.

Nonpecuniary predictors of tax compliance are often referred to as "tax morale." Torgler and Schaffner (2007) identify numerous factors which contribute to tax morale, and therefore, to compliance in excess of that predicted under deterrence theory. These factors include tax administration, tax system, tax awareness, compliance perceptions, trust in officials and others, and willingness to obey. Luttmer and Singhal (2014) review this literature and argue that while tax morale is traditionally used as a single concept, it is more accurately organized as a set of underlying motivations for tax compliance. However, a taxpayer's tax morale can be demonstrated through a number of different mechanisms: intrinsic motivation, reciprocity, peer effects and social influences, cultural factors, information imperfections and deviations from utility maximization (i.e. perceived probability of detection may exceed actual probability, loss aversion, etc.). Using structural equation modeling, Niesiobedzka (2014) predicts and finds that procedural tax fairness, or taxpayers' belief that the taxing authority engages in supportive and respectful procedures, directly affects tax morale and indirectly affects tax compliance via tax morale.

Fairness

Recent work by Farrar et al. (2020) suggests that researchers' use of fairness has been limited given a reliance on the use of the fairness concept as borrowed from the organizational literature. The authors argue that context is requisite in the conceptual understanding of fairness, and without defining fairness specifically in the tax context, use of the concept in research is limited. This study surveyed approximately 501 taxpayers in the United States across broad demographics and conducted an exploratory factor analysis (EFA) in order to define the underlying dimensions of the latent construct of tax fairness. The EFA produced three distinct dimensions of tax fairness, including fairness of the tax assessment process, exchange equity, and vertical equity.[3] These results narrow dimensions of tax fairness identified by a previous study (Gerbing 1988), which included general fairness, exchange with government, attitude toward taxes of the wealthy, progressive versus flat tax system, and self-interest.

As referenced by Farrar et al. (2020), use of the fairness concept has been limited in tax research. Though Trivedi et al. (2003) do not specifically measure tax fairness in their experiment studying the impact of personal and situational factors on taxpayer compliance, they conclude that "[tax authorities] reinforce the concept of fairness of the tax system among tax

[3] Of the three dimensions produced by the EFA, the first dimension (Fairness of the tax assessment process) has three sub-dimensions which include (1) even-handedness of the tax authority's procedures, (2) adequacy of explanation from the tax authority, and (3) respectful treatment from the tax authority (Farrar et al. 2020).

payers" (p.175). Maroney, Rupert, and Wartick (2002) conduct an experiment to examine if providing taxpayers with various explanations (e.g. explanations of exchange equity, vertical equity, and horizontal equity) increases the perceived fairness of the tax. The authors find that the exchange equity explanation most consistently produced a positive effect on perceptions of tax fairness, but that the current taxability of the taxpayer was influential in determining which explanations were effective. Fairness has been studied in contexts outside of the United States. Hartner-Tiefenthaler, Kubicek, Kirchler, Rechberger, and Wenzel (2012) study a sample of European taxpayers and find that the relationship between tax paying behavior and outcome favorability is mediated by distributive fairness of the tax system.

Procedural Fairness

As found in the factor analyses discussed above, tax fairness is a multi-dimensional item. This study examines the perceptions of fairness as it relates more specifically to the IRS audit selection procedures, which fall under the dimension of "fairness in the tax assessment process," and more specifically, the sub-dimension of "even-handedness of the tax authority's procedures" (Farrar et al. 2020). This is often referred to as "procedural fairness," or "procedural justice," in the literature. Leventhal (1980) defines procedural fairness as "an individual's perception of the fairness of procedural components of the social system that regulate the allocative process (p.16)." Thibaut and Walker (1975) note that people desire fair procedures because they believe that fair procedures produce fair distributions. Tyler (1987) built on this theory, stating that people care to express their opinions on the fairness of procedures, even when the procedures are not directly linked to an outcome, but rather to contribute toward a "value-expressive" worth. The expression of opinions is an important component of feeling respected, even beyond imparting influence on the decision-making process.

As it relates to the context of audit selection, procedural fairness in this case would be valued in that it produced a fair allocation of audits across all taxpayers. Leventhal (1980) identifies six procedural justice rules that define the criteria to be satisfied for an allocative process to be considered fair[4]. Complicating the matter is that individuals not only individually weigh these rules differently in their perceptions of fairness, but may also themselves weigh these rules differently situationally. Criticism of the IRS' use of data mining and advanced technologies has focused on issues such as lack of transparency in algorithms, lack of notice to taxpayers, privacy concerns, and the potential for prejudice in algorithms. These concerns are reflective of some of Leventhal's rules for procedural justice; if a taxpayer held up the bias-suppression rule as most valuable, accusations of discrimination in audit selection algorithms[5] would be problematic. For taxpayers with privacy concerns, the IRS' use of data mining with limited transparency and no taxpayer notice might violate the ethicality rule of these procedures.

However, other rules have more complex interpretations as it relates to these IRS audit selection procedures. The consistency rule, for example, might be held up as supportive of algorithmic, machine-determined audit selection, in that it relies on predictive data rather than random chance in its process. In contrast, some taxpayers might feel that data mining inconsistently and inappropriately identifies "on-the-grid" taxpayers as more likely audit targets than those taxpayers with a smaller digital footprint.

Wenzel (2002) defines procedural fairness in the tax context as the respect, trustworthiness, and neutrality in the tax assessment process. Wenzel surveys a sample of

[4] Leventhal (1980) defines the six procedural rules as follows: (1) Consistency, (2) Bias-suppression, (3) Accuracy, (4) Correctability, (5) Representativeness, and (6) Ethicality.
[5] For example, Houser and Sanders (2017) posit a scenario where minorities have higher than normal medical expenses, flagging a potential for unusual deductions. If these patterns are learned by algorithms, this correlation might result in the unfair targeting of minorities for audits. Rubin (2020) also notes risks if algorithms for audit selection inadvertently discriminate against taxpayers based on race or location.

Australian taxpayers and finds that the relationship between procedural fairness and tax compliance varies based on the form of tax compliance. For pay-income reporting and tax minimization, tax compliance is determined by self-interest variables (i.e. excluding justice), but for nonpay income and the claiming of deductions, tax compliance is determined by both self-interest and justice variables. The impact of justice on tax compliance is strongest for individuals with a strong national identity. Hartner, Rechberger, Kirchler, and Schabmann (2008) investigate survey data from the Community, Hopes, Fears, and Actions Survey and the Australian Tax System – Fair or Not Survey (in years 2000 and 2001-02, respectively) and conduct a structural equation model, strengthening the link between taxpayers' perceptions of procedural justice and their motivations to comply (or not) with tax policies, and further, its influence on tax compliance.

Hypotheses

As the research indicates, perception of procedural tax fairness can be an important contributor to the intrinsic motivation to comply with tax policies. Several articles have provided critical evaluations of how the IRS' use of big data analytics and advanced technologies will affect fairness (Harvard Business School 2018; Houser and Sanders 2017), the latter of which claims that privacy concerns related to these methodologies are so pervasive that they break the law. At this point, however, an experimental analysis to assess how taxpayers will respond in both their perceptions of fairness and their tax compliance given the knowledge of the IRS' use of big data analytics and advanced technologies in audit selection procedures has not yet been conducted.

As the IRS' use of artificial intelligence becomes more widespread, knowledge of this use has begun to spread. Houser and Sanders (2017) document that the IRS now engages in the data mining of public and commercial (e.g. social networking sites) data pools and creates detailed taxpayer profiles from which they can run data analytic software in order to aid in audit selection. Vijayan (2010) reported that, via documents procured through the Freedom of Information Act, the IRS confirmed their use of social networking sites to collect information from taxpayers, going as far as to include this type of data mining in their agent training. Dean Silverman, then the IRS' senior advisor to the commissioner for the Office of Compliance Analytics, also confirmed that the IRS is expanding its source data for taxpayer profiles to include PayPal, social media, and other internet data (Houser and Sanders 2017). These reports clarify the ways in which the IRS obtains publicly available data from the internet in order to better operationalize their data analytics program in improving audit selection procedures.

In light of predicted privacy concerns with the IRS' "problematic" use of big data analytics in its audit selection procedures, we expect that perceptions of procedural tax fairness will mediate the relationship between the IRS' audit selection procedures and tax compliance. Formally stated:

> **H1:** Procedural tax fairness will mediate the relationship between IRS audit selection procedures and tax compliance.

This study hypothesizes a moderated mediation model where the detection risk of income moderates the direct relationship between the IRS' audit selection procedures and perceptions of procedural tax fairness and the indirect relationship between the IRS' audit selection procedures and tax compliance. Specifically, we operationalize detection risk of income by manipulating the traceability of income and predict that when income is less traceable, the IRS' use of big data analytics will elicit a decrease in the perception of procedural tax fairness such that the increased probability of detection does not influence compliance behaviors. When income is more traceable, we expect the IRS' use of big data analytics to be a more salient encouragement to comply. Formally stated:

> **H2:** Income traceability will moderate the mediating effect of procedural tax fairness on the association between IRS audit selection procedures and tax compliance, such that the negative effect of IRS audit selection procedures on procedural tax fairness is stronger when income is less traceable.

III. METHODOLOGY

This section details the experimental design, participants, experimental procedures and task, operationalization of independent and dependent variables, and control variables.

Design

We test our hypotheses with a 2 x 2 between-subjects experiment. We manipulate the IRS' audit selection procedures on two levels: basic technologies (e.g. document matching), and big data analytics and artificial intelligence (e.g. social networking site data mining). Participants will be informed in a brief message as described below about the IRS' audit selection procedures for each condition prior to their completion of the current year tax return. We also manipulate the income traceability of the contract work done on two levels: work obtained through word-of-mouth recommendations with low traceability, and work obtained through social media advertising with high traceability.

Participants

Participants were taxpayers from the United States recruited through Amazon Mechanical Turk. Participants were paid a flat wage of $1.30 for completion of the task. Following Peer, Vosgerau, and Acquisti 2013 and LaMothe and Bobek 2020, we required participants have completed at least 1,000 Human Intelligence Tasks (HITs), have at least a 95% approval rate on previously completed HITs, and pass the screening questions required for our study (e.g. US citizens that have previously filed a US tax return). We requested 100 participants (approximately 25 participants per cell) and received a total of 98 usable responses after adjusting for correct responses to the attention check. Descriptive statistics for the demographic measures gathered are presented in Table 1.

Experimental Procedures and Task

In this experimental scenario adapted from LaMothe and Bobek (2020), participants are given information about fictitious taxpayer Parker[6] and asked to respond to questions regarding this information. Participants are first instructed that Parker is readying to prepare a 2020 tax return using the tax software program SpeedyTax, and are then told of Parker's income situation for the current year, which includes traditional W-2 wages from an employer and cash contract income from various side work. Participants are then directed to the SpeedyTax software program, which opens with a message from the IRS regarding their audit selection methods. Participants are prompted to indicate the amount of contract income that they believe Parker would report. They are then asked to put themselves in Parker's position and indicate the amount of contract income that they would report if they were in the same situation[7].

In response to the scenario, participants are asked to respond to several questions, including the likelihood of audit of Parker's tax return, the likelihood of detection of any unreported income upon audit of Parker's tax return, Parker's perceptions of procedural tax

[6] Given the potentially sensitive nature of the dependent variables (perceptions of procedural tax fairness and tax compliance), the scenario is stated and the dependent variables are posed in the third-person so as to reduce the influence of social desirability bias (Chung and Monroe 2003). This approach is consistent with prior literature in this area (LaMothe and Bobek 2020, Farrar et al. 2020). In addition, participants were asked to rate their agreement with two statements designed to measure social desirability bias at the conclusion of the instrument.
[7] The results remained statistically similar between first- and third-person phrasing, so we focus on the analysis of responses to the third-person questions to remain consistent with the phrasing of our instrument.

fairness, attention checks, demographic measures, and open-ended questions as to why or why not participants would report the cash income if in Parker's position.

Independent Variables

IRS Audit Selection Procedures

This study attempts to illuminate some of the consequences of the IRS' use of big data analytics and artificial intelligence in its audit selection methods. Therefore, we draw on actual IRS audit selection methods[8] to inform our operationalization of this variable. We manipulate IRS audit selection methods in two ways: basic technologies and big data analytics and artificial intelligence. Both conditions include a reminder message within the tax software program regarding the audit selection methods the IRS currently employs. The basic technologies condition states that "the IRS continues to develop its audit selection methods by use of" traditional technologies such as document-matching and previously audited tax returns. The big data analytics and artificial intelligence condition states that the "IRS is using new sources of data to develop its audit selection methods by use of" advanced technologies such as artificial intelligence and new sources of data such as data from online payment systems such as Venmo and PayPal and data from social media sites such as Facebook and Twitter. Both conditions conclude that the IRS uses these methods to "better ensure taxpayer compliance."

Income Traceability

Income traceability represents the detection risk of contract income based on how the work was obtained. We manipulate income traceability in two ways: low traceability and high

[8] Sources used in informing the audit selection methods specified in the instrument included the IRS website, academic articles (e.g. Houser and Sanders 2017), and news articles (e.g. Harvard Business School 2018, Vijayan 2010).

traceability. In both conditions, Parker completes a number of local side projects in addition to traditional employment. The low traceability condition details that Parker obtained these side projects "using word-of-mouth recommendations from prior clients and friends." The high traceability condition details that Parker "posted on Facebook Marketplace, Twitter, and Instagram to advertise this work" to secure side projects. In both conditions, Parker earns the same amount of income collected in various cash payments throughout the year.

Dependent Variables

Tax Compliance

After seeing the information discussed above, participants are asked to respond to three questions regarding tax compliance. In accordance with the tax software context, participants are first asked to report into SpeedyTax the amount of the contract income that they think Parker would report. This primary dependent variable precedes two additional measures of tax compliance, which ask first how certain a participant is regarding the income that Parker would report and second how much of the income the participant would report if in Parker's position. The primary dependent variable is measured as the dollar amount of contract income reported by the participant.

Procedural Tax Fairness

Perceptions of procedural tax fairness are measured as the factor score of a participant's response to an adaptation of the Procedural Tax Fairness Scale (PTFS) (Tyler 1987, van Dijke and Verboon 2010). This adaptation uses three statements from this scale and one additional statement tailored to the context of our experiment, for a total of four statements. After the conclusion of the tax compliance task, participants are asked to indicate the degree to which

Parker would agree with the following statements: (1) The IRS treats people as if they have honestly declared their taxes, (2) The IRS uses fair procedures in determining its selections for audits, (3) The IRS makes sure to have the necessary information available to make decisions, and (4) The IRS treats everyone in the same manner[9].

Control Variables

Demographic measures were collected at the end of the research instrument for age, gender, education, income, political beliefs, and previous taxpayer and IRS audit experience, following prior literature (e.g. Tittle 1980; Jackson and Milliron 1986; Houston and Tran 2001; Bobek, Roberts, and Sweeney 2007; Verboon and van Dijke 2007) and the specific research context. As demonstrated in the bivariate analysis presented in Table 2, none of these demographic variables were significantly correlated with tax compliance, and we therefore excluded these variables from the main model.

IV. RESULTS

Tests of Hypotheses

We test a moderated mediation model examining the mediating role of procedural fairness on the relationship between IRS audit selection procedures and tax compliance at varying levels of income traceability. Results from these tests are presented in Tables 3 through 5.

H1 Testing

[9]A confirmatory factor analysis (CFA) confirmed that these four measures converged on one factor as indicated by primary factor loadings ranging from 0.66 to 0.89. No secondary factor loadings exceeded 0.20. Observation of the scree plot confirmed our expectation of convergence on one factor. Therefore, the factor score for each participant was used as the primary measure of procedural tax fairness in the analysis.

Table 3 presents the results of the moderated mediation model, which includes analysis of the mediating effect of procedural tax fairness on the relationship between IRS audit selection procedures and tax compliance. As observed by these results demonstrated pictorially in Panel A and tabulated in Panel B, there is a significant and negative relationship between IRS audit selection procedures (*X*) and procedural tax fairness (*M*) (β= -0.70, p<.01) and a significant positive relationship between procedural tax fairness (*M*) and tax compliance (*Y*) (β= 603.03, p<.01). Importantly, the presence of the mediator in the model results in a nonsignificant direct relationship between the independent variable IRS audit selection procedures and the dependent variable tax compliance (β= 661.12, p=0.11), providing evidence of the mediating effect of procedural tax fairness. This provides support for hypothesis 1.

That the coefficients of the components of the mediating relationship differ directionally, but are both significant, indicates that the IRS' use of advanced technologies in audit selection is associated with a decrease in perceptions of procedural tax fairness, while, in line with prior literature, perceptions of procedural tax fairness are associated with increased tax compliance. The resultant effect on tax compliance for each condition is explored further in the supplemental analysis.

H2 Testing

Table 3 also presents results of the full moderated mediation analysis, where income traceability (*W*) moderates the relationship between the independent variable IRS audit selection procedures (*X*) and the mediator procedural tax fairness (*M*). Here, we observe a significant interaction effect (*X* * *W*) (β= 0.93, p=0<.01) with a positive coefficient, indicating that the effect of IRS audit selection on perceptions of procedural tax fairness is *strengthened* when income is more traceable. Said another way, if the detection risk of income is higher, an increase in the detection risk of audit procedures further decreases taxpayers' perceptions of procedural fairness. The index of moderated mediation (560.07) is significant with a bootstrap confidence interval entirely above zero (45.09 to 1318.36), evidence of a significant moderated mediation model that indicates the conditional indirect effects of IRS audit selection procedures on tax compliance as moderated by procedural tax fairness vary significantly based on income traceability. These findings provide support for hypothesis 2.

To further understand these effects under varying levels of income traceability, we run a simple effects analysis at each level of income traceability (Table 4, low traceability and Table 5, high traceability). Table 4 observes the results of the simple effects model when income was less traceable, or the contract income was advertised through word-of-mouth. At this value of income traceability, the effect of IRS audit selection procedures on procedural tax fairness is negative and significant (β= -0.070, $p<.01$). This indicates that when income is less traceable, the IRS' use of advanced technologies in their audit procedures are more likely to diminish perceptions of tax fairness. However, the effect of procedural tax fairness on tax compliance is only marginally significant (β= 576.51, $p<.10$) and the indirect effect of IRS audit selection procedures on tax compliance is not significant, with a bootstrap confidence interval between -1156.46 and 47.80.

Table 5 observes the results of the simple effects model when income was more traceable, or the contract income was advertised through social media sites. At this value of income traceability, the effect of IRS audit selection procedures on perceptions of procedural tax fairness is *not significant* (β= 0.23, p=0.39). We posit that the difference in this main effect at different levels of income traceability is due, perhaps, to a perception of the detection risk. When income traceability is low, detection risk of income is comparatively low. Therefore, when the detection risk of audit increases, this has a more significant influence on perceived *overall* detection risk and therefore heightens the effect on perceptions of procedural tax fairness. In contrast, when income traceability is high, detection risk of income is already high, thereby negating the marginal effect of the increase in detection risk of audit, and decreasing the resultant effect on perceptions of procedural tax fairness.

Further, the effect of the effect of procedural tax fairness on tax compliance is only marginally significant (β= 648.33, p<.10) and the indirect effect of IRS audit selection procedures on tax compliance is not significant, with a bootstrap confidence interval between -126.52 and 692.45.

Supplemental Analysis

Given that our full model evidenced a significant moderated mediation model where income traceability moderated the relationship between IRS audit selection procedures and perceptions of procedural tax fairness, but the individual simple effects models did not produce significant mediation models, we conducted additional analysis into the resultant influence on tax compliance of each condition in order to provide a clearer interpretation of the effect of the IRS' use of advanced technologies on compliance.

Tables 6 and 7 present the results of this supplemental analysis, where Table 6 depicts the interactive effect of income traceability and IRS audit selection procedures on the dependent variable of procedural tax fairness, and Table 7 depicts this interactive effect on the dependent variable of tax compliance.

Table 6 observes that when income traceability is high, taxpayers' perceptions of procedural tax fairness are not altered by IRS audit selection procedures (t(44)=-0.878, p=.192, one-tailed). When income traceability is low, taxpayers' perceptions of procedural tax fairness are significantly lower (t(50)=2.694, p<.01, one-tailed) in the advanced technologies condition as compared to the basic technologies condition. We posit that to those in the low income traceability condition, perceived detection risk of income is lower, and therefore the IRS' use of advanced technologies and concurrent increase in the detection risk of audit is more salient as compared to those in the high income traceability condition to whom the perceived detection risk of income is already high.

Table 7 observes that when income traceability is low, IRS audit selection procedures have no significant effect on tax compliance, where a mean of $2,919 is reported in the basic technologies condition versus a mean of $3,124 reported in the advanced technologies condition (t(50)=-0.347, p=.365, one-tailed). However, when income traceability is high, the IRS' use of advanced technologies in audit selection procedures result in marginally significantly higher tax compliance with a mean of $3,517 income reported as compared to a mean of $2,686 reported in the basic technologies condition (t(44)=-1.407, p<.10, one-tailed).

Taken together, we find that when income is more traceable, the IRS' use of advanced technologies is associated with a marginally significant 16 percent increase in tax compliance and no significant effect on perceptions of procedural fairness; when income is less traceable, the IRS' use of advanced technologies has no significant influence on tax compliance, but decreases perceptions of procedural tax fairness by a statistically significant 14 percent. Though an increase in tax compliance and tax collections is clearly the goal of the IRS' use of big data analytics and advanced technologies, the IRS should be aware of possible unintended consequences on tax morale, specifically as it relates to the underreporting of less traceable income. That knowledge of the IRS' use of advanced technologies did not itself motivate increased tax compliance when income traceability was low should be of note to the agency, as less traceable income already comprises a high percentage of the tax gap.

V. DISCUSSION

The use of big data analytics and other advanced technologies in detecting tax evasion and determining audit selection has been hailed as a remedy to budget concerns at the IRS, but these procedures have been criticized for their lack of notice to taxpayers, lack of transparency in the algorithms, potential for discrimination, and privacy concerns. While these procedures have the potential and certainly the intent of increasing compliance via broader identification of non-filers, this study provides evidence of an accompanying decrease in perceptions of procedural tax fairness when income traceability is low. We find that when income is more traceable, the IRS' use of advanced technologies is associated with a marginally significant 16 percent increase in tax compliance and no significant effect on perceptions of procedural fairness; when income is less traceable, the IRS' use of advanced technologies has no significant influence on tax compliance, but decreases perceptions of procedural tax fairness by a statistically significant 14 percent. Though an increase in tax compliance and tax collections is clearly the goal of the IRS' use of big data analytics and advanced technologies, this accompanying decrease in perceptions of procedural tax fairness should be of interest to the IRS, as prior literature has found an association between perceptions of tax fairness and willingness to comply with tax policy (Hartner et al. 2008).

The primary contribution of this study is to experimentally examine taxpayer reaction to the IRS' use of big data analytics in its audit selection procedures. While the IRS has been using these practices for over a decade, US taxpayers are increasingly aware of privacy concerns and systemic discrimination. This paper provides evidence on how taxpayers will respond in both their perceptions of procedural tax fairness, and in their compliance more directly, to knowledge of this usage.

This study is subject to certain limitations. Participants recruited through MTurk may be more technologically advanced than the general population and this may limit the generalizability of the findings. Further, the dependent variable of tax compliance might be of a personal nature to participants, decreasing their willingness to respond honestly. To address this concern, social desirability of participants' is measured and tested as a covariate in the model.

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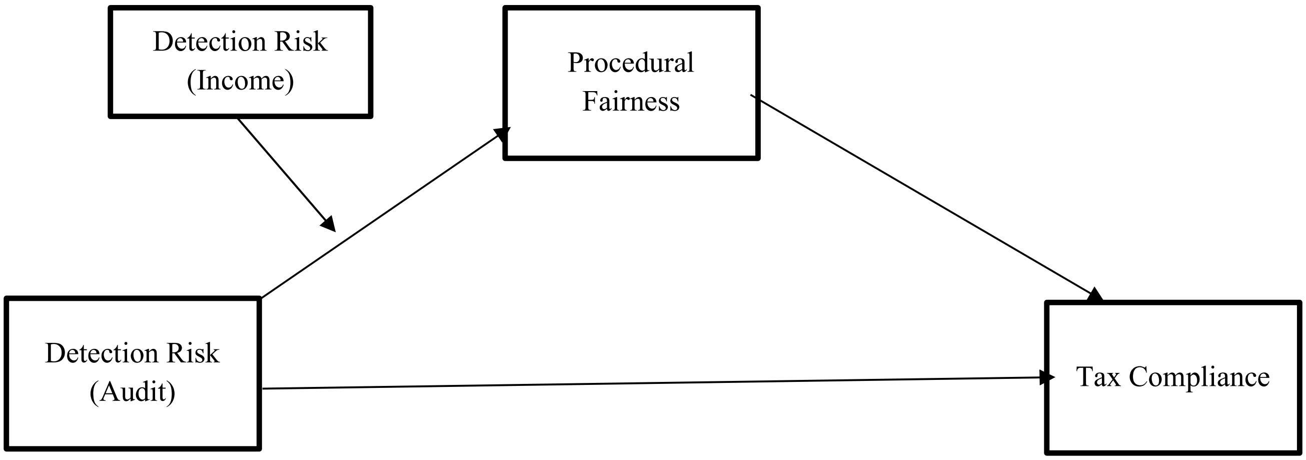
APPENDIX

Figure 1:

Panel A: Theoretical Model



Panel B: Study-Specific Model

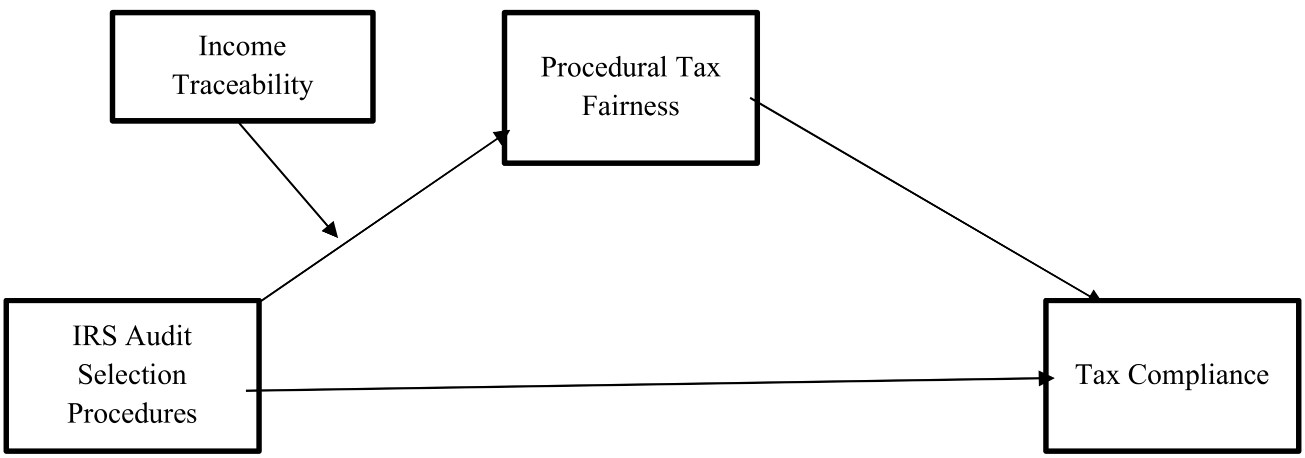


Table 1

Demographic Profile Statistics

	Number	Percentage
Sample Size	98	100.0
Gender		
Male	53	54.1
Female	44	44.9
IRS Audit Experience?		
Yes, within 5 years	14	14.3
Yes, more than 5 years ago	5	5.1
No	78	79.6
Age:		
18-34	43	43.9
35-54	46	46.9
55-74	9	9.2
Household Income:		
Less than $25,000	12	12.2
$25,000 – 50,000	29	29.6
$50,000 – 75,000	28	28.6
$75,000 – 100,000	20	20.4
More than $100,000	9	9.2
Highest Level of Education Completed:		
Some high school	1	1.0
High school/GED	15	15.3
Some college	17	17.3
2-year college	8	8.2
4-year college	43	43.9
Advanced degree	13	13.3
Political Beliefs:		
Democrat	39	39.8
Moderately left-leaning	16	16.3
Independent	21	21.4
Moderately right-leaning	9	9.2
Republican	13	13.3

Note: As we did not force responses to any demographic questions, participants may have opted out of these responses. Therefore, percentages may not total 100 percent for each category.

Table 2

Bivariate Correlations

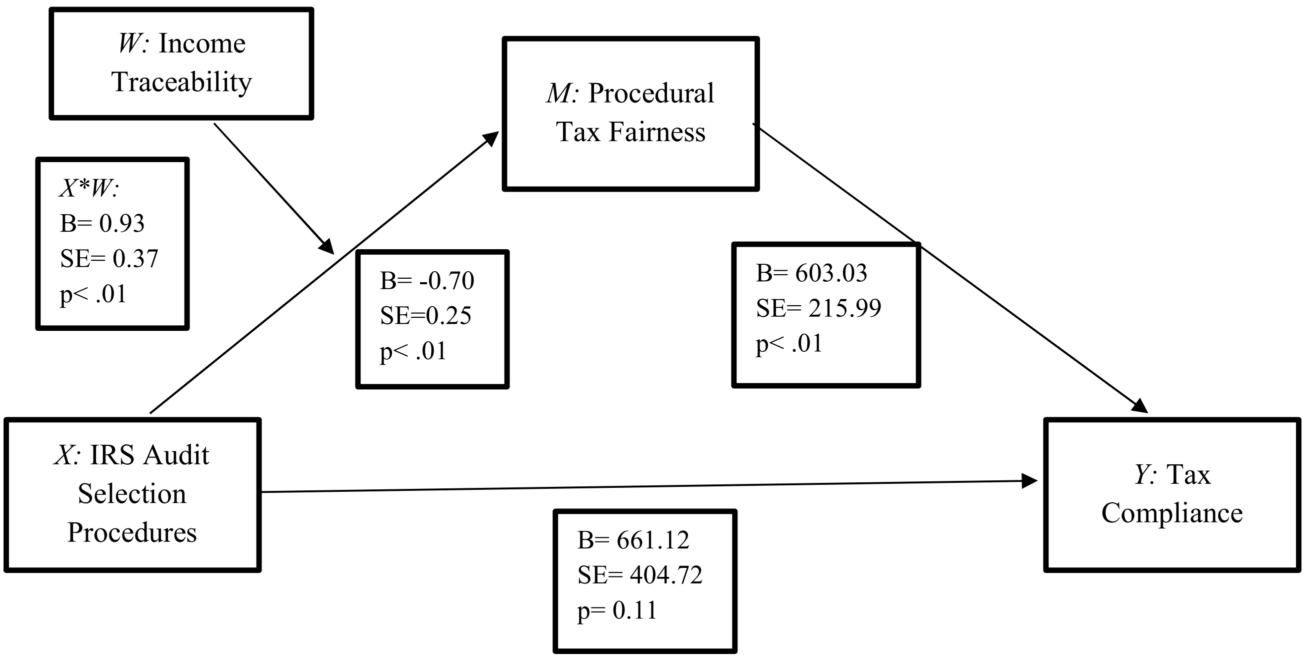
	Income Traceability	PTFS	IRS Message	Tax Compliance	Gender	Audit	Age	Income	Education	Political Affiliation
Moderator Income Traceability	1									
Mediator PTFS	-.10	1								
IV IRS Message	.02	-.14	1							
DV Tax Compliance	.02	.25***	.12	1						
Demographic Variables Gender	-.20**	.08	-.08	.05	1					
IRS Audit Experience	.16	.03	.06	.03	.02	1				
Age	.08	.16	-.06	.05	-.08	-.07	1			
Income	-.04	.17*	-.08	-.06	-.10	.13	0.14	1		
Education	.04	.16	-.04	.07	.20**	.26***	-.26**	.35***	1	
Political Affiliation	.07	.04	.04	.12	.08	.06	.11	.19	-.04	1

*, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 3

Moderated Mediation Analysis: Income Traceability as Moderator (*W*) and Procedural Tax Fairness as Mediator (*M*) of IRS Audit Selection Procedures (*X*) and Tax Compliance (*Y*)

Panel A: Main Model



Panel B: Total Sample Primary Statistical Analysis

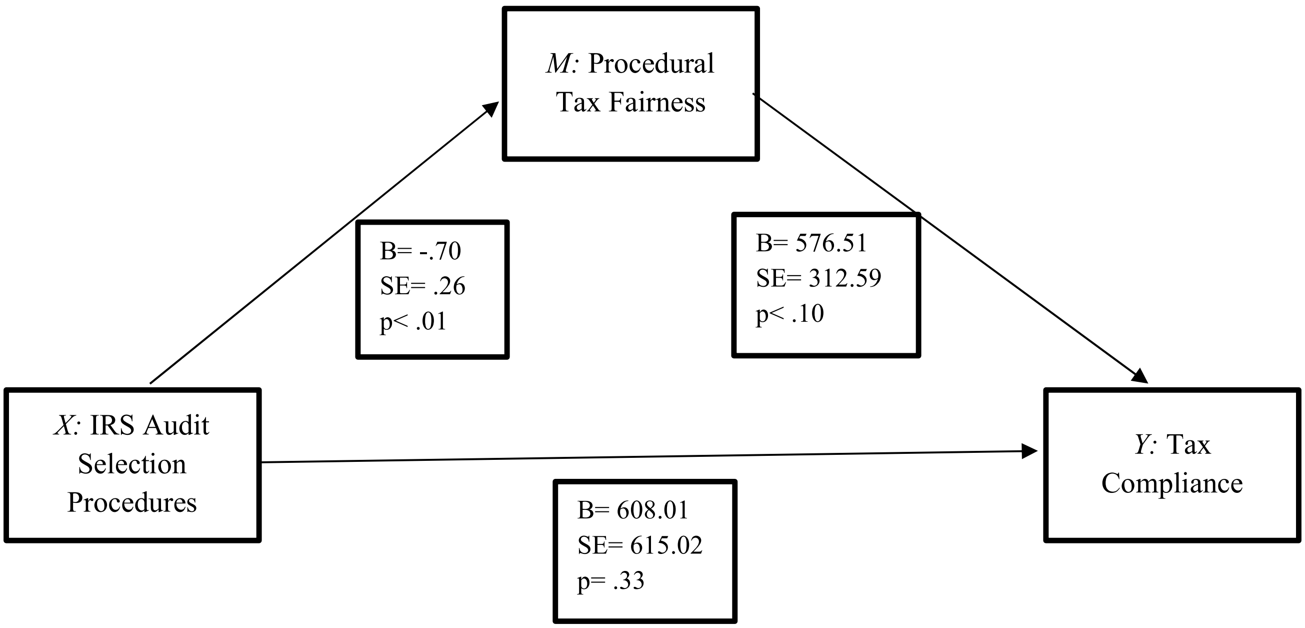
	Consequent					
	M **(Procedural tax fairness)**			***Y*** **(Tax compliance)**		
Antecedent	**Coeff.**	**SE**	**p-value**	**Coeff.**	**SE**	**p-value**
X	-0.70	0.25	<.01	661.12	404.72	.11
W	-0.62	0.25	<.05	-	-	-
X * *W*	0.93	0.37	<.01	-	-	-
M	-	-	-	603.03	215.99	<.01
Constant	0.41	0.17	<.05	2736.32	275.79	<.01
R^2	9.1%			9.0%		
F	(3, 94) = 3.14			(2, 95) = 4.68		
p-value	<.05			<.01		
Index of moderated mediation = 560.07 (SE 334.32). A bootstrap confidence interval based on 10,000 bootstrap samples was entirely above zero (45.09 to 1318.36), evidence that the moderated mediation model is significant. The conditional indirect effects of IRS audit						

selection procedures on tax compliance through procedural tax fairness vary significantly based on income traceability.

Table 4

Simple Effects Analysis for Low Income Traceability Condition (Word-of-Mouth Advertising): Procedural Tax Fairness (*M*) of IRS Audit Selection Procedures (*X*) and Tax Compliance (*Y*)

Panel A: Simple Effects Model for Low Income Traceability



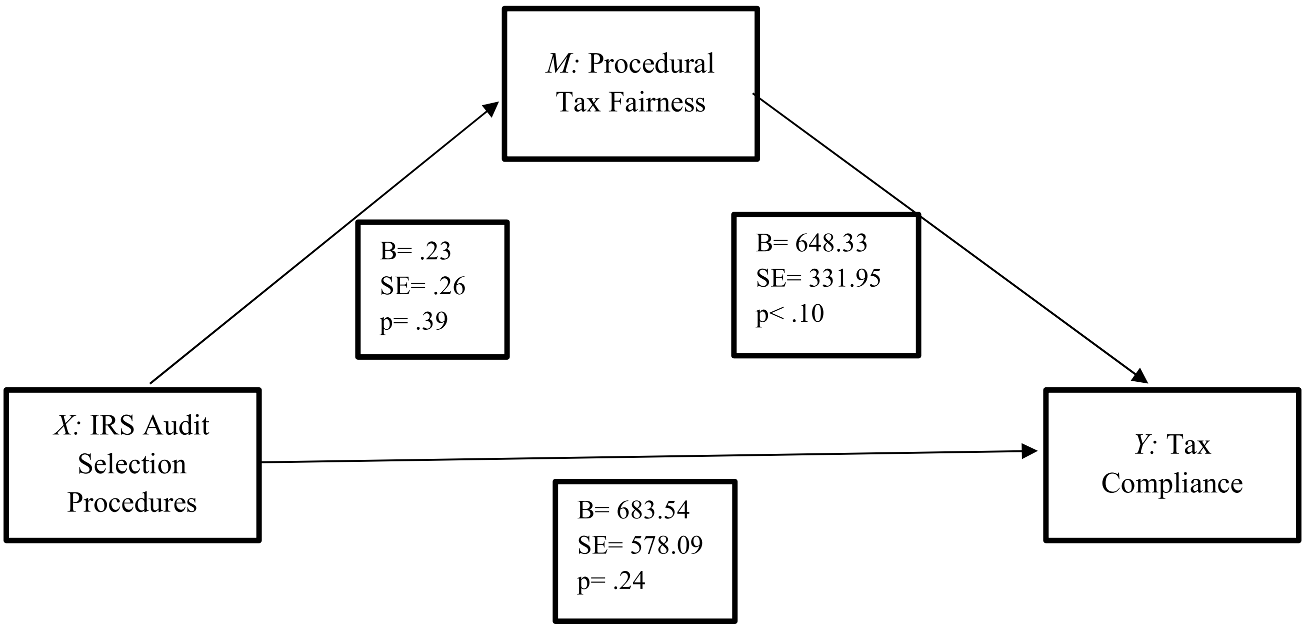
Panel B: Main Analysis

	Consequent					
	M **(Procedural tax fairness)**			***Y*** **(Tax compliance)**		
Antecedent	**Coeff.**	**SE**	**p-value**	**Coeff.**	**SE**	**p-value**
X	-0.70	0.26	<.01	608.01	615.02	.33
M	-	-	-	576.51	312.59	<.10
Constant	0.41	0.18	<.05	2682.48	411.10	<.01
R^2	12.7%			6.7%		
F	(1,50) = 7.25			(2,49) = 1.76		
p-value	<.01			0.18		
The indirect effect of *X* (IRS Audit Selection Procedures) on *Y* (Tax Compliance) is negative (-403.76) but not significant (a bootstrap confidence interval based on 10,000 bootstrap samples was between 0 (-1156.46 to 47.80). This suggests that IRS audit selection procedures are not significantly associated with tax compliance when income traceability is low.						

Table 5

Simple Effects Analysis for High Income Traceability Condition (Social Media Advertising): Procedural Tax Fairness (*M*) of IRS Audit Selection Procedures (*X*) and Tax Compliance (*Y*)

Panel A: Simple Effects Model for High Income Traceability



Panel B: Main Analysis

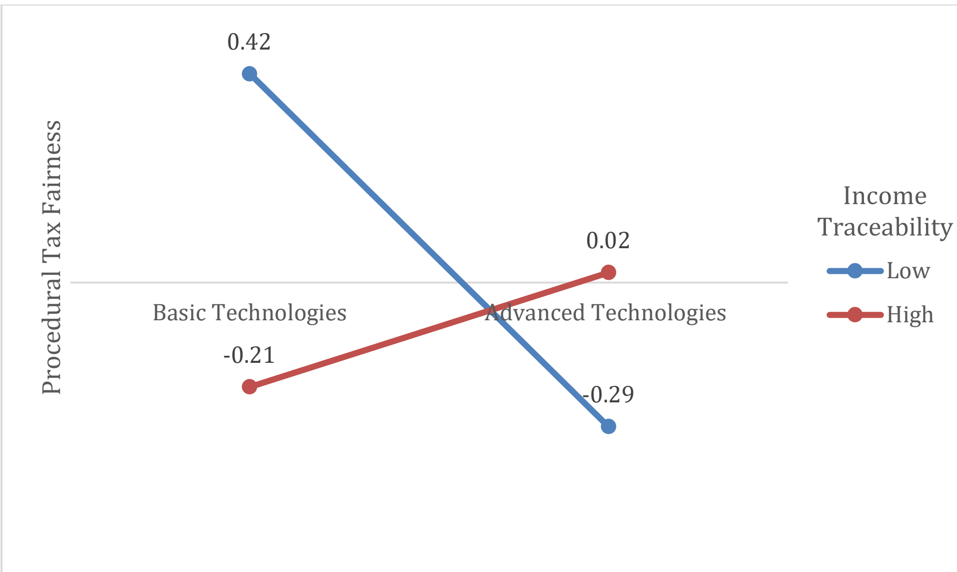
	Consequent					
	M **(Procedural tax fairness)**			***Y*** **(Tax compliance)**		
Antecedent	**Coeff.**	**SE**	**p-value**	**Coeff.**	**SE**	**p-value**
X	0.23	0.26	.39	683.54	578.09	.24
M	-	-	-	648.33	331.95	<.10
Constant	-0.21	0.18	.25	2821.34	402.36	<.01
R^2	1.2%			12.1%		
F	(1,44) = 0.77			(2,43) = 2.96		
p-value	.39			<.10		

The indirect effect of *X* (IRS Audit Selection Procedures) on *Y* (Tax Compliance) is positive (148.08) but not significant (a bootstrap confidence interval based on 10,000 bootstrap samples was between 0 (-126.52 to 692.45). This suggests that IRS audit selection procedures are not significantly associated with tax compliance when income traceability is high.

Table 6

Interactive Effect of Income Traceability and IRS Audit Selection Procedures on Procedural Tax Fairness

Panel A: Graph of Interactive Effect of Income Traceability and IRS Audit Selection Procedures on Procedural Tax Fairness



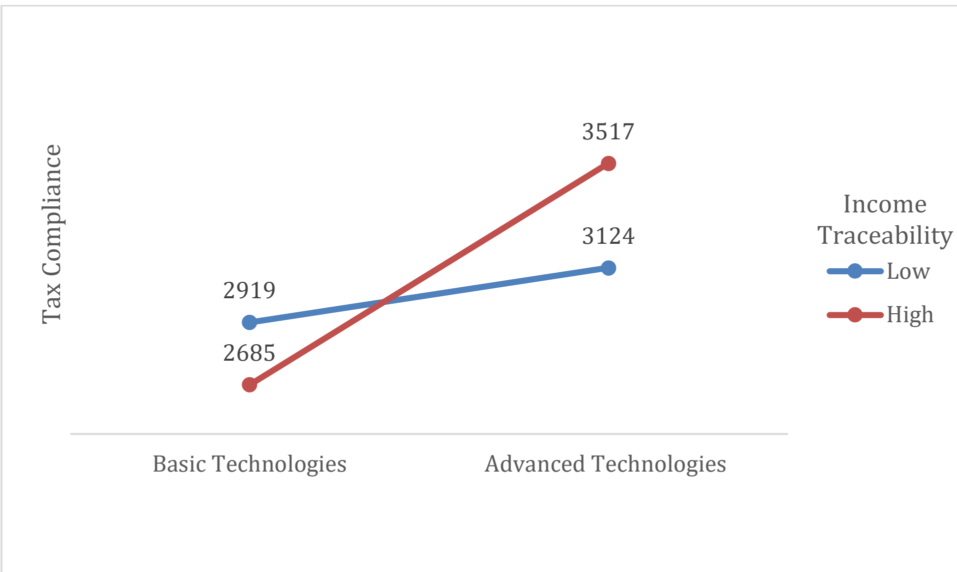
Panel B: Cell Means (Standard Deviation)

		IRS Audit Selection Procedures		
		Basic Technologies	Advanced Technologies	t-stat (df)
Income Traceability	Low (Word-of-Mouth Advertising)	0.42 (0.88) n= 28	-0.29 (0.99) n= 24	2.694 (50) p<.01
	High (Social Media Advertising)	-0.21 (0.93) n= 24	0.02 (0.82) n= 22	-0.878 (44) p=.192
	t-stat (df)	2.460 (50) p<.01	-1.142 (44) p=.130	

Table 7

Interactive Effect of Income Traceability and IRS Audit Selection Procedures on Tax Compliance

Panel A: Graph of Interactive Effect of Income Traceability and IRS Audit Selection Procedures on Tax Compliance



Panel B: Cell Means (Standard Deviation)

		IRS Audit Selection Procedures		
		Basic Technologies	Advanced Technologies	t-stat (df)
Income Traceability	Low (Word-of-Mouth Advertising)	2919.75 (2108.23) n= 28	3124.00 (2123.20) n= 24	-0.347 (50) p=.365
	High (Social Media Advertising)	2685.79 (2141.74) n= 24	3517.41 (1838.52) n= 22	-1.407 (44) p<.10
	t-stat (df)	0.396 (50) p=.347	-0.669 (44) p=.254	