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The Effects Of Eligibility Complexity And Incentive Structure On Taxpayer Behavior

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THE EFFECTS OF ELIGIBILITY COMPLEXITY AND INCENTIVE STRUCTURE ON TAXPAYER BEHAVIOR

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ABSTRACT

Policymakers often use tax incentives to encourage desirable taxpayer behavior, and researchers from multiple disciplines provide evidence that these incentives lead to behavioral change. A new stream of literature focuses on the factors that affect the extent to which tax incentives achieve this goal, with specific emphasis on the factor of complexity. This study expands this literature by investigating the effect of eligibility determination complexity and tax incentive structure on the relationship between incentives and taxpayer behavior. Based on the findings from research on the take-up of social benefits, I predict and find some evidence that taxpayers are more likely to respond to a tax incentive when determining eligibility for the incentive is less complex. In response to preferences for the credit structure in legal and economics literature and a similar preference in the business press, I predict, but do not find, that taxpayers are more likely to respond to a tax incentive structured as a credit versus an economically equivalent deduction. However, I do find evidence to suggest that structure is important when eligibility determination complexity is high – taxpayers seem to be less likely to behave as incentivized given an increase in eligibility determination complexity in a credit structure. This finding of a significant interaction between a form of complexity and incentive structure should motivate researchers to include a manipulation of incentive structure in future complexity studies. Results of my study should also be of interest to tax policymakers at various levels of government as I find evidence suggesting a wholesale switch in tax incentives to the credit structure (a change advocated by many legal and economics researchers) could weaken taxpayer response when the credit features high eligibility determination complexity.

DEDICATION

To my wife and son, my mom and dad, and my mother-in-law and father-in-law. Thank you for your unwavering support and encouragement from start to finish.

LIST OF ABBREVIATIONS AND SYMBOLS

ACA	Affordable Care Act
ANCOVA	Analysis of Covariance
CHIP	Children's Health Insurance Program
EITC	Earned Income Tax Credit
HIT	Human Intelligence Task
IRC	Internal Revenue Code
IRS	Internal Revenue Service
MTR	Marginal Tax Rate
MTurk	Amazon Mechanical Turk
RQ	Research Question
TCJA	Tax Cuts and Jobs Act
US	United States

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I. INTRODUCTION

While the primary goal of the United States (US) tax system is the generation of revenue to fund the activities of government, the Internal Revenue Code (IRC) is frequently used to encourage (discourage) behavior deemed desirable (undesirable) by Congress. These behavioral changes are incentivized through preferential tax rates, income exclusions, deductions, and/or credits. Because the goal of these tax incentives is to change taxpayer behavior, it is important to gain a greater understanding of factors that impact the extent to which these incentives are effective in changing taxpayer behavior. Researchers have recently focused their attention on one such factor – complexity (Morrow and Rupert 2015, Bobek, Chen, Hageman, and Tian 2016, Morrow, Stinson, and Doxey 2018). The primary goal of this study is to extend this research by further investigating the role of complexity in the relationship between tax incentives and taxpayer behavior. Specifically, I aim to determine whether differences in the difficulty of determining eligibility for a tax incentive and differences in tax incentive structure affect the extent to which a tax incentive changes taxpayer behavior. Per Slemrod (2005), "there is no consensus regarding what constitutes complexity" (281). For the purpose of this paper, complexity refers to the difficulty a taxpayer faces when interacting with tax laws that establish tax incentives. This includes, for example, difficulty encountered in determining eligibility for a tax incentive, in determining the timing of the tax incentive, and in determining the actual tax effect of the tax incentive through tax calculations.

The idea that complexity can affect the extent to which taxpayers change their behavior in response to tax incentives is logical and intuitive. In fact, studies cited above provide some evidence that complexity affects taxpayer behavior when a certain behavior is incentivized. However, complexity in the tax environment is multi-faceted and can be operationalized in a study in various ways. To better understand how complexity moderates the relationship between tax incentives and taxpayer behavior, more research is required. My study answers the call of Bobek et al. (2016) for additional research to determine the effects of different forms of complexity.

In this study I predict that taxpayers will be more likely to respond to tax incentives when determining eligibility for the incentive is less complex. I refer to this continuum of complexity going forward as "eligibility determination complexity." Researchers in other (non-accounting) disciplines have studied a similar variable under a different name – "hassle" costs – and have found evidence to suggest it significantly (negatively) affects the take-up[1] of social benefits programs like the Children's Health Insurance Program (CHIP), the Earned Income Tax Credit (EITC), and Medicaid (Currie 2006, Bertrand, Mullainathan, and Shafir 2006, Bhargava and Manoli 2015). The stakes are often quite high for the individuals eligible to participate in these means-tested programs – a choice not to participate will almost certainly have a negative impact on the well-being of families involved. Taxpayers responding to tax incentives that generally encourage the spending of discretionary income will likely have significantly less to lose when choosing not to behave as incentivized, so I expect these taxpayers will also be affected by eligibility determination complexity.

I also predict that taxpayers will be more responsive to tax incentives structured as tax credits (as compared to tax deductions). A strong preference exists for the credit structure on the grounds of equity and efficiency in economics and legal literature (Batchelder, Goldberg Jr., and

[1] "Take-up" refers to the rate at which individuals eligible to receive benefits through a given program actually pursue and apply for those benefits.

Orszag 2006, Batchelder 2017, Stegmaier 2008, Furman 2008, Fischer and Huang 2013), with frequent calls for all tax incentives to be structured as (refundable) credits. Similarly, writers in business press (Steber 2016, Lankford 2007) tend to favor the credit structure, often advising readers to focus their attention and effort on credits instead of deductions.

Finally, I explore as a research question whether changes in eligibility determination complexity differentially affect incentives structured as credits versus deductions. Research on the effect of incentive structure on taxpayer behavior is quite limited, so it is difficult to predict the existence and nature of an interaction between forms of complexity and incentive structure. The studies addressing complexity have generally held constant the tax incentive structure, so finding evidence of this interaction could extend our understanding of the effect of complexity on taxpayer response to tax incentives.

I address my research questions and test my hypotheses by conducting an experiment. My experimental setting is adapted from Morrow and Rupert (2015), which uses a hypothetical purchase decision setting to investigate the effect of complexity (specifically, complexity in the form of conformity between federal and state tax laws and complexity in the form of incentive tax effect calculation complexity) on taxpayer purchasing decisions. Participants are asked to assist a friend who is finalizing a vehicle purchase decision, which has been narrowed to two similar and equally-acceptable alternatives – a traditional (gas) vehicle and a hybrid vehicle. Participants make their recommendations (the operationalized dependent variable of interest) after considering the cost and features of each vehicle and the economic value of a tax incentive. The incentive is manipulated in eligibility determination complexity (low complexity vs. high complexity) and in incentive structure (credit vs. deduction), resulting in a 2×2 between-participants experimental design.

Addressing these research questions using an experimental methodology is appropriate for two important reasons. The experimental methodology allows me to analyze the effects of the variables of interest while holding constant the content (i.e., purpose, goals) and the economic effect of the tax incentive. To capture the effect of eligibility determination complexity and/or incentive structure using existing data (i.e., publicly-available IRS data), the same tax incentive would need to be offered simultaneously to taxpayers in multiple structures and varying levels of eligibility determination complexity. But, taxpayers respond to tax incentives structured as credits *or* deductions – they are not allowed to choose their preferred structure. Further, some incentives set forth by the IRC are relatively similar in purpose, but have significantly different rules, limits, and exceptions, which lead to different economic outcomes across incentives.

I find that eligibility determination complexity does significantly affect taxpayer response to tax incentives under some modeling conditions. Participants in multiple subsamples responding to an incentive featuring low eligibility determination complexity provided recommendations significantly more in favor of the tax-incentivized hybrid model than those responding to an incentive featuring high complexity. However, I do not find evidence to support my prediction that taxpayers will be more likely to respond to tax incentives structured as tax credits versus tax deductions. I find some evidence of differences in taxpayer feelings toward the two structures as participants assigned to groups featuring a credit structure indicate a significantly greater level of certainty regarding the actual tax effect of the tax incentive encountered in the task than those in groups featuring a deduction structure. Lastly, although I do not find evidence to suggest that participants were influenced by incentive structure *alone*, I find some evidence in various subsamples of interest of an interaction of these two variables –

the effect of eligibility determination complexity on the dependent variable appears, in some cases, to depend on the tax incentive structure.

Understanding the extent to which eligibility determination complexity affects the relationship between tax incentives and taxpayer behavior is important for multiple reasons. First, a taxpayer facing a behavioral decision involving a tax incentive can often consider eligibility for a given tax incentive without consideration of detailed tax calculations and estimations. Considering eligibility, therefore, is likely easier for a taxpayer to consider *before* making the decision than many other factors in the tax incentive decision context. Understanding the effect of eligibility determination complexity on taxpayer behavior is also important to policymakers. If a tax incentive is created with the intent of changing taxpayer behavior, policymakers should be concerned about the possibility that some taxpayers will underreact to the incentive because of the complexity they encounter in determining their eligibility. Legitimate reasons certainly exist to justify some level of complexity in the eligibility requirements associated with a tax incentive – avoiding abuse, targeting subsets of the taxpaying population, etc. However, my study provides some evidence that even modest increases in eligibility determination complexity could be detrimental to the effectiveness of a tax incentive.

Policymakers should also be concerned about how tax incentive structure affects taxpayer response to a given tax incentive. Consideration of the structure of current and past tax incentives leaves open questions regarding policymaker decisions about these structures. As mentioned above, I find some evidence to suggest that complexity (eligibility determination complexity in my study) may affect tax incentives structured as credits, but not deductions. This, combined with the finding of a significant difference in certainty mentioned above, reveals that taxpayers respond differently to different tax incentive structures, which should inform the legislative process for new tax incentives and re-designs of existing incentives. Policymakers, it seems, should consider an approach that favors the tax credit structure when policy goals can be achieved with low eligibility determination complexity, but favors the tax deduction structure when higher levels of eligibility determination complexity are required.

The remainder of this paper is structured as follows: Chapter II provides background information, a review of applicable literature, and develops hypotheses; Chapter III details the research methodology and design; Chapter IV details the analysis of results; and Chapter V provides a conclusion.

II. BACKGROUND AND HYPOTHESIS DEVELOPMENT

Background

Policymakers generally choose from two available methods for encouraging desirable taxpayer behavior - direct government subsidies and incentives delivered through the Internal Revenue Code (commonly referred to as "tax expenditures"). While the direct government subsidy approach entails sending cash payments directly to taxpayers, the tax expenditure approach is different. Instead of encouraging citizens with an incentive in the form of cash, this approach offers an incentive in the form of a reduced tax bill.[2] In their book, *Taxes in America: What Everyone Needs to Know*, Leonard Burman and Joel Slemrod present an argument for why politicians prefer to run programs through the IRC. Tax expenditures, they explain, are **not** considered spending for budget purposes, and this lower level of public scrutiny makes them a much more politically attractive tool to encourage desirable taxpayer behavior (Burman and Slemrod 2013, 150-151).

Examples of behavior deemed desirable and incentivized by policymakers abound in the IRC. Home ownership is considered to be desirable – that is, our society benefits from increased home ownership. So, taxpayers were once allowed to reduce their tax bills through a tax incentive that encouraged home purchases by first-time homebuyers. Charitable giving provides funding to charitable organizations providing goods and services that would otherwise require

[2] An example of the government incentivizing desirable behavior directly is subsidy payments made to farmers to encourage the planting of certain crops or to encourage no planting to allow fields to "rest." Examples of "tax expenditures" include tax incentives such as income exclusions for health insurance premium payments and tax credits related to the pursuit of higher education.

direct government spending through government programs. This substitution has been deemed desirable, so taxpayers see their taxes reduced by amounts donated to qualifying charitable organizations. Entrepreneurship and risk-taking has been deemed desirable and is encouraged through opportunities to reduce taxes via relaxed limitations on losses incurred on small business stock.

Researchers have devoted significant attention to determining the extent to which the incentives delivered through the nation's tax system actually affect taxpayer behavior. Two such incentives – an incentive to encourage charitable giving (Peloza and Steel 2005, Duquette 2016) and an incentive to encourage investment in research and development (Bloom, Griffith, and Van Reenen 2002, Wilson 2009) - have garnered a great deal of attention from researchers in various disciplines. This research leads to significant evidence supporting the effectiveness of tax incentives in changing taxpayer behavior.

Factors Affecting Taxpayer Reaction to Tax Incentives

Researchers in a recently-developing stream in the accounting literature, it seems, rely on the results of the studies above and begin with the baseline assumption that tax incentives do indeed influence taxpayer behavior. Their focus shifts from whether tax incentives influence behavior to uncovering factors that affect the *extent* to which these incentives can change taxpayer behavior. Morrow et al. (2018), for instance, examine (among other things) the effect of various demographic factors (age and experience with filing tax returns) on the effectiveness of a tax incentive aimed at encouraging participation in the health insurance exchanges that resulted from the Affordable Care Act (ACA).

My study answers a call for additional research by Bobek et al. (2016) to better understand the effect of another factor affecting the relationship between tax incentives and taxpayer behavior - complexity. Morrow and Rupert (2015) initiated this stream of literature with a study that investigates the effect of a type of tax incentive complexity – federal / state tax law conformity – on taxpayer reaction to incentives aimed at encouraging the purchase of a certain type of vehicle. Results of the study indicate that participants are more likely to consider purchasing a hybrid vehicle (instead of a nearly-identical traditional gas-burning vehicle) when federal and state tax incentives that encourage such behavior are similar (conforming) instead of dissimilar (non-conforming). The study by Bobek, et al. (2016) followed and investigates the effect of complexity on taxpayer reaction to tax incentives using a different variation of complexity – choice complexity. Participants were encouraged to participate in a training program that could lead to higher earnings with incentives that reduced the cost of the program, either choosing from a few incentive options or many. Results suggest that the number of choices available for the same incentivized behavior (choice complexity) does not affect the likelihood of an individual choosing the incentivized behavior, but that more choice complexity does lead to errors in an individual's ability to determine optimal choices.

These two studies that addressed the effect of complexity on taxpayer response to tax incentives operationalized complexity in very different manners. These differences in approach illuminate the fact that complexity is multi-faceted. In their call for further research, Bobek et al. (2016) offer several suggestions as additional facets of complexity possibly worth exploration. My study investigates one such suggestion – complexity related to an individual determining eligibility to take advantage of a tax incentive, hereafter referred to as eligibility determination complexity.

Eligibility Determination Complexity

Eligibility determination complexity varies widely among tax incentives – one can easily determine eligibility to take advantage of the deduction for educator expenses. However, determining eligibility to take advantage of the EITC can be a daunting task.[3] Researchers in various disciplines have addressed the idea of eligibility determination complexity (sometimes referred to as "hassle") indirectly in the context of the take-up of social benefits. The fact that many social programs (Medicaid programs, welfare-type programs, etc.) have low levels of take-up is somewhat surprising as most of the media attention on these programs seems to be reserved for abuse in the form of individuals improperly receiving benefits. Researchers with economics, public policy, and various other backgrounds have studied this take-up phenomenon extensively. Per Currie (2006), the literature seems to agree that individuals that are eligible but choose not to receive social program benefits make that choice for one or more of three reasons – "stigma, transactions costs, and lack of information." The costs associated with enrolling in various social programs is of particular interest in this study and is worth additional consideration.[4]

To introduce and motivate her literature review, Currie (2006) points to Moffitt's (1983) traditional economic model, which incorporates stigma as a cost that impacts an eligible individual's utility maximization when deciding whether to enroll in welfare. Currie (2006), however, states that more recent literature "suggests that other costs associated with the takeup

[3] A comparison of relevant IRS Publications for the 2018 tax year reveals that taxpayers eligible for the deduction for educator expenses are described using one sentence (see IRS Publication 529 at: https://www.irs.gov/pub/irs-pdf/p529.pdf) while taxpayers eligible for the EITC are described through an "EIC Eligibility Checklist" that includes twelve steps and references to fifteen rules (see IRS Publication 596 at: https://www.irs.gov/pub/irs-pdf/p596.pdf).

[4] While stigma is certainly a factor deserving attention in the arena of public insurance and welfare programs, it almost certainly would not be an important factor when considering most of the behaviors incentivized through the IRC. Lack of information about tax incentives could play a more important role in the relationship between a tax incentive and a taxpayer's behavioral decision, but the amount of information presented in this study will be held constant (see below in the Methodology and Design chapter).

of social programs are more important than stigma," such as "costs of learning about, and applying for the programs" (Currie 2006, 6). Similarly, Bertrand et al. (2006) points to three factors that can affect take-up in addition to stigma – knowledge/understanding of the program by targeted recipients, "hassle factors" that serve as demotivation, and procrastination.

Some of the work by researchers in other (non-accounting) disciplines has actually addressed the take-up of a social benefit that is delivered through the IRC and functions much like the tax incentives considered in this study.[5] The EITC is, per the IRS (2019a), a "benefit for working people who have low to moderate income." More specifically, Burman and Slemrod (2013), refer to the EITC as "one of the largest antipoverty programs in the United States" (8). The EITC suffers, like many other social programs, from lower-than-expected take-up. In fact, the most recent IRS estimates indicate that a range of approximately 77 to 80 percent of taxpayers eligible to receive EITC benefits actually received benefits during the 2015 tax year, which means approximately 21 percent of eligible individuals did not receive any benefits (IRS 2019c). Bhargava and Manoli (2015) send follow-up information to EITC-eligible non-claimants in California, manipulating the presentation of various information regarding eligibility and other program characteristics, and find that take-up increased significantly when program information was more (instead of less) visually appealing and eligibility requirements were more concisely listed.

Although traditional economics models have largely viewed them as inconsequential, factors like hassle costs and complexity associated with determining eligibility have been found to be more important than expected in affecting behavioral decisions in social program take-up.

[5] This study focuses on tax incentives aimed at changing taxpayer behavior. The EITC can only be claimed by individuals that earn income during a tax year. So, the EITC would only be considered a tax incentive to the extent that it is aimed at encouraging working behavior in the subset of the population with the lowest levels of income.

The potential consequences of failing to take advantage of a benefit offered through a social program can be serious for these individuals and their families. The individuals eligible for these means-tested programs are, by definition, around or below the poverty line in most cases. Choosing not to take advantage of a program such as the EITC could literally lead to a family not having enough food to eat during a given year. If small hassle costs like complex eligibility requirements deter these at-risk eligible individuals from taking up available benefits from social programs, the same may be true for individuals responding to tax incentives that encourage desirable behaviors when these decisions almost exclusively involve a taxpayer's discretionary income. Therefore, I make the following prediction:

H1: Individuals will be more (less) likely to engage in a tax-incentivized behavior when determining eligibility for the incentive is less (more) complex.

Tax Incentive Structure

Tax incentive structures – exclusions, deductions, and credits – are all aimed at decreasing the amount of tax owed by a taxpayer, and all have been tapped by Congress to incentivize taxpayer behavior changes. The decrease in tax, however, is achieved differently through each incentive structure. In the simplest possible terms, income tax in the US is calculated as follows: economic income is reduced by income exclusions to yield gross income; gross income is reduced by deductions to yield taxable income; tax is a function of taxable income and marginal tax rates; tax is reduced by tax credits and tax prepayments (tax withholding and estimated tax payments) to yield actual tax due. Income exclusions reduce tax by reducing the amount of economic income a taxpayer is required to include in gross income, which reduces taxable income and ultimately reduces tax. Deductions reduce tax by directly reducing taxable income, which ultimately reduces tax. Finally, tax credits reduce tax due "directly" on a "dollar-for-dollar" basis, with the reduction in tax occurring after tax has been initially calculated on taxable income. See Figure 1 below for an illustration of this calculation.

Figure 1

Simplified Explanation of the Individual Income Tax Calculation

	Income from all sources (economic income)
less:	Items specifically excluded from income
equals:	Gross income
less:	Deductions
equals:	Taxable income
	Progressive tax rates applied
equals:	Tax (before considering credits)
less:	Tax credits and tax prepayments (i.e., withholding on salaries and wages)
equals:	Tax or refund due with return

Another important difference in these tax incentive structures is each incentive's relationship to marginal tax rates. The economic value of an incentive delivered as an income exclusion or a deduction is directly influenced by a taxpayer's marginal tax rate. The same dollar amount of income exclusion or deduction reduces tax by different amounts for two taxpayers subject to different marginal tax rates. Discussion / consideration of income exclusions is omitted going forward for two reasons. First, income exclusions and deductions reduce tax in similar manners. Secondly, income exclusions are certainly a large category of tax incentives, but generally are reserved for tax incentives involving income earned (i.e., the income exclusion for municipal bond interest earned) instead of money spent. For income exclusion items that do involve spending, any administrative burden falls on employers (i.e., income exclusion for amount of income spent on health insurance premiums) of the taxpayers that benefit from the incentives.

The economic value of an incentive delivered as a tax credit is not influenced by marginal tax rates. The same dollar amount of tax credit reduces tax by the same amount for two taxpayers subject to different marginal tax rates. For illustration purposes, it is helpful to consider two single taxpayers with income levels and, therefore, marginal tax rates on opposite ends of a spectrum. If the first taxpayer has taxable income of $900,000, that taxpayer's marginal tax rate in the 2019 tax year would be 37 percent. If the second taxpayer has taxable income of $9,000, that taxpayer's marginal tax rate in the 2019 tax year would be 10 percent. So, one additional dollar of deduction reduces the wealthy taxpayer's tax by 37 cents while one additional dollar of deduction reduces the low-income taxpayer's tax by 10 cents. One dollar of credit, on the other hand, would reduce each taxpayer's tax by one dollar.

When analyzing tax incentive structure, relevant literature can be found in a wide array of disciplines. Some accounting researchers have focused on whether behavior is most effectively modified through tax incentives or through other methods of reducing the net cost of a choice. Most recently, Stinson et al. (2018) provided evidence that tax credits are only as effective as price discounts offered by retailers to encourage a purchasing behavior when the price difference between the incentivized product and a standard alternative is high (price discounts are more effective when price difference is low).

Most of the research in this area has been offered by economists and legal experts focusing on which structure is *theoretically* more appropriate. Very little research, however, has provided empirical evidence regarding each structure's effectiveness in changing taxpayer behavior in the incentivized direction. One recent study by Morrow et al. (2018) provides evidence that young individuals critical to the success of the Affordable Care Act (ACA) would have been more likely to change their health insurance purchasing behavior in response to a tax incentive delivered as an increase / decrease in deductions instead of the credit / surcharge system created through the ACA. This finding has important implications in the tax incentive literature and additional work is needed to provide broader evidence of the effect tax incentive structure has on an incentive's ability to change taxpayer behavior.

Tax credits, as detailed above, affect an individual's tax bill differently than tax deductions. The fact that deductions reduce tax due by the product of the deduction and the taxpayer's marginal tax rate is undisputed. One dollar of tax credit is, indeed, more valuable than one dollar of tax deduction. Policymakers, however, do not deliver tax incentives in a manner that gives taxpayers a choice between a tax credit and a tax deduction for the *same* incentive. A given tax incentive is delivered as a tax credit *or* a tax deduction. An incentive delivered as a tax credit will almost certainly include a limit that reduces the tax effect of the incentive to an amount similar to the tax effect that would result from the same incentive delivered as a deduction. Consider, for example, a hypothetical case of policymakers deciding to change the structure of the tax incentive for qualified home mortgage interest from deduction to credit. A taxpayer that traditionally deducts $20,000 per year in mortgage interest leading to tax savings of $5,000 (assuming a 25% marginal tax rate) should expect to be allowed a $5,000 credit such that total tax savings are equal without regard to incentive structure.

A stream of literature addressing taxpayers' understanding of and ability to use marginal tax rates in decision-making began with Gensemer, Lean, and Neenan (1965), which provided evidence of a general lack of awareness of marginal tax rates among many high-income taxpayers. The study called attention to the possibility that economists' assumptions of full taxpayer awareness of marginal tax rates could be invalid, stating that "Such exercises in economic theory are significant only to the extent that taxpayers are in fact aware of their marginal tax rates and changes in the rates" (Gensemer et al. 1965, 258). Several studies followed providing additional evidence that taxpayers are either unaware of or unable to accurately estimate their marginal tax rates (Fujii and Hawley 1988, Rupert and Fischer 1995), and that greater marginal tax rate visibility (Rupert and Wright 1998) and lower levels of complexity in the tax system affecting marginal tax rate determinations (Rupert, Single and Wright 2003) improves taxpayer decision-making.

Another important and related empirical question to be considered, however, is whether taxpayers are differentially affected by tax incentives structured as deductions or credits when both structures yield identical reductions in tax (i.e., the economic value of the incentive is held constant across incentive structures). We might consider whether a taxpayer in the top tax bracket for 2019 (a 37 percent marginal tax rate) responding to a $7,500 tax credit that incentivizes the purchase of a fully-electric vehicle would be more or less likely to respond to a $20,270 tax deduction ($20,270 x 37 percent marginal tax rate = $7,500 tax savings) incentivizing the same purchase. These incentives are economically equivalent, yielding the same decrease in tax - $7,500. Traditional economic models that assume individuals are fully rational would suggest that taxpayers facing these circumstances would be equally likely to respond to the incentive without regard to the incentive structure. As mentioned above, however, very few researchers have sought empirical evidence to support this fully rational behavior and freedom from heuristics and biases.

There are some reasons to expect taxpayers to respond more favorably to deductions than credits. Morrow et al. (2018) did not make directional predictions, but did suggest that inexperienced taxpayers might be heavily influenced by the fact that deduction amounts will be, by design, significantly higher in nominal value than credit amounts that reduce tax by the same dollar amounts (i.e., a $1 credit is economically equivalent to a $4 deduction at a 25% marginal tax rate). Morrow et al. (2018) also provides some evidence that certain taxpayers, specifically young, inexperienced taxpayers, are more likely to respond to deductions than credits in a health insurance context. Finally, some evidence exists in favor of deductions in the allocation of tax incentives across structures – per Batchelder (2017), 78 percent of tax expenditures costs in the 2016 tax year stemmed from deductions, exclusions, or deferrals while only 13 percent of costs stemmed from tax credits.[6]

There are, however, multiple reasons to expect taxpayers to look more favorably upon tax credits. First, several previously-cited studies provide evidence that taxpayers are unaware of or unable to accurately determine their marginal tax rates. The relationship between marginal tax rates and deductions is detailed above. This intermediate step in calculating the economic impact of a tax incentive could lead to uncertainty and an aversion to the deduction structure that might not exist with the credit structure. A portion of my study answers a call for research by Rupert and Fischer (1995) to "examine the extent to which taxpayer behavior is affected by uncertainty about the MTR" (53).

Secondly, researchers in multiple disciplines often advocate in favor of the credit structure over other incentive structures. Some researchers favor credits for the sake of efficiency. Batchelder et al. (2006) and Batchelder (2017) indirectly discuss the definition of an efficient tax incentive to be an incentive that jointly maximizes social benefits (the positive behavioral change(s) resulting from the tax incentive) and minimizes cost in terms of reduced tax

[6] The remaining 9 percent stemmed from "reduced rates on savings income" (Batchelder 2017).

revenues. Batchelder et al. (2006) advocates strongly in favor of refundable tax credits[7], claiming that tax incentives should benefit all households uniformly "unless the balance of the evidence suggests that more social benefits are generated by certain households engaging in the behavior than by others or that certain households are more responsive" (47). Stegmaier (2008) argues that refundable tax credits are preferable in higher education incentives because other structures fail to encourage targeted taxpayers (those in low-income families) to pursue higher education. These low-income families will be unlikely to send students to college without the benefit of an incentive while middle- and higher-income families (those most likely to send students to college without regard to tax incentives) are the only beneficiaries of education incentives structured as deductions and nonrefundable credits.

While efficiency arguments focus on which taxpayers are and are not receiving benefits as well as the cost associated with those benefits, others present a closely-related argument in favor of the credit structure based on equity.[8] Many have argued that wealthy taxpayers should not yield more tax benefit per dollar of deduction than taxpayers with lower levels of income (a function of marginal tax rates). This feature of our tax system, they claim, does not fit with our emphasis on progressivity or vertical equity – the idea that taxpayers with greater abilities to pay should pay more tax. Furman (2008) casts a spotlight on this inequity in the realm of health insurance tax incentives and Fischer and Huang (2013) call the deduction allowed for qualified home mortgage interest "ripe for reform," advocating for a change in the incentive structure from deduction to credit. Batchelder (2017), in a testimony delivered before the Senate Committee on

[7] Most tax credits are non-refundable, but several refundable credits exist in the IRC. A non-refundable credit can reduce tax due, but can never be used to reduce tax below zero. A refundable credit can be used to effectively reduce tax due below zero, which could result in a refund that is larger than tax prepayments (i.e., withholding and estimated tax payments).

[8] There is considerable overlap in research that advocates for the credit structure for the sake of efficiency and research that advocates for the credit structure for the sake of equity.

Finance in 2017, made the case that all tax incentives should be delivered as refundable tax credits to end this relationship between the economic value of tax incentives and marginal tax rates. Other calls to end this inequity come from presidential advisors as can be seen in reports issued by commissions charged by President George W. Bush and President Barack Obama to generate ideas for tax reform. The Bush commission's report presented plans aimed at preserving vertical equity by "shifting some tax preferences from deductions, which tend to benefit high-income households, to tax credits, which benefit all taxpayers equally" (The President's Advisory Panel on Federal Tax Reform 2005, xv). The Obama commission's report similarly advocated this switch, calling for the elimination of all itemized deductions with some incentives added back to the IRC in the form of credits (The National Commission on Fiscal Responsibility and Reform 2010).

Another reason to expect taxpayers to be more responsive to credits is that writers in business press generally have written about tax incentives in a manner that favors credits. Tax credits are generally portrayed to be less complex and more valuable than tax incentives structured as deductions. One example of this message being delivered through the business press can be found in an article written by the Chief Tax Officer for Jackson Hewitt Tax Service (someone that can reasonably be assumed to understand tax incentives). He wrote an article for the *Huffington Post* with a title that represents a gross over-simplification of tax incentives – "Tax Deductions are Good, But Tax Credits Are Better" (Steber 2016). After referencing an earlier article that discussed commonly-missed itemized deductions, Steber wrote the following:

> "Deductions though, whether standard or itemized, only reduce your amount of taxable income. Credits however are figured AFTER your tax liability and therefore, reduce your tax bill dollar for dollar. Credits are not only good, they are better than deductions and there are a lot of them." (Steber 2016)

Another example can be found in a 2007 *Kiplinger* article with a similar title – "Tax Credit vs. Deduction: If you have to choose one or the other, take the credit – it's worth more" (Lankford 2007).

Finally, there is limited evidence of policymaker bias in favor of the credit structure. There are very few cases of tax incentives being converted from one structure to another. Two such transitions, however, both featured tax incentives originally structured as deductions being transitioned to credits. First, the clean-fuel vehicle deduction was in effect through the 2005 tax year but was converted to the hybrid vehicle tax credit beginning with the 2006 tax year (Sallee 2011). Secondly, an itemized deduction allowed for child and dependent care expenses was converted to a credit under the Tax Reform Act of 1976. In a document prepared by the Staff of the Joint Committee on Taxation, the *General Explanation of the Tax Reform Act of 1976*, the conversion occurred to ensure the incentive was "available to those who use the standard deduction as well as to itemizers and so that it will provide the same tax relief to taxpayers in low brackets as to those in high brackets" (Staff of the Joint Committee on Taxation 1976, 7). This language matches the theoretical justifications for favoring credits provided by economic and legal researchers that was detailed above (efficiency and equity). The brief explanation is void, however, of documentation of policymaker consideration of the structures' effectiveness in changing taxpayer behavior.

Based on this evidence, I posit that the average taxpayer will view the tax credit structure more favorably and will be more likely to change his/her behavior in response to the tax credit structure. Therefore, I make the following prediction:

H2: Individuals will be more (less) likely to engage in a tax-incentivized behavior when the tax incentive is structured as a tax credit (tax deduction).

Relationship between eligibility determination complexity and tax incentive structure

It is possible that eligibility determination complexity and tax incentive structure are related and jointly affect a taxpayer's response to a tax incentive – that eligibility determination complexity affects incentives structured as credits differently than those structured as deductions. Given the lack of empirical research investigating the effect of tax incentive structure on taxpayer response to incentives, it is difficult to predict *ex ante* the existence and nature of an interaction. Since tax incentives are so frequently structured and delivered as credits or deductions, finding evidence of an interaction should inform future research on taxpayer response to tax incentives. The early studies that address the effect of complexity on the relationship between tax incentives and taxpayer behavior feature designs that do not manipulate the structure of the incentive. Morrow and Rupert (2015) employ a design which holds constant the incentive structure, while Bobek et al. (2016) use an abstract setting with no mention of incentive structure. Developing a more thorough understanding of how complexity affects this relationship in different incentive structures is an important next step. Morrow et al. (2018) provided some initial evidence of the importance of incentive structure, but more research is needed to expand our understanding of this variable. Therefore, I will investigate the following research question:

RQ: Does the effect of eligibility determination complexity on taxpayer response to tax incentives depend on tax incentive structure?

III. METHODOLOGY AND DESIGN

I address my research questions by conducting an experiment, employing a 2×2 between-participants design. The experiment consisted of a simple judgment and decision-making task aimed at modeling the decision environment faced by a taxpayer incentivized to behave in a certain manner consistent with what has been deemed desirable. The experimental design is an adaptation of Morrow and Rupert (2015), which involves a vehicle purchase decision. I administered the experimental instrument through Qualtrics. Participants were randomly assigned to one of four conditions that varied by tax incentive structure (credit / deduction) and eligibility determination complexity (low complexity / high complexity).

Experimental Procedures

Participants first provided consent and were asked to assume the role of someone helping a friend make a vehicle purchase decision. Participants were then informed that a friend purchasing a new vehicle has narrowed their decision to two choices and has asked for input. This design feature is different from the Morrow and Rupert (2015) design, which asked participants to assume the role of someone considering their own purchase of a new vehicle. I made the design choice to use the "helping a friend" approach to avoid the problematic experimental tactic of telling participants to assume their personal income is a certain number (see discussion on income below). Following Morrow and Rupert (2015), participants were told that the two vehicles are similar in all aspects important to the friend making the purchase decision, and the critical difference is that one option is a traditional (gas) model while the other option is a hybrid model. Style, handling, and acceleration for each model is said to be acceptable to the friend while reliability, safety, insurance costs, warranty and maintenance programs, purchase method (cash instead of financing), and resell timing and value are all consistent between the two options, and held constant across all conditions. Limited information on purchase price, sales tax, fuel efficiency, and operating costs were presented to participants in all conditions, with a reference to a detailed specifications list to come on a later screen.

Across all conditions, the two combinations of purchase price, sales tax, and five-year cost to fuel the vehicle were constructed such that the two options were basically identical in undiscounted total cost after considering tax savings. The estimated five-year cost to power each vehicle was based on 12,000 miles of travel per year (60,000 miles total over the five year period). For the traditional (gas) model, given fuel efficiency of 28 miles per gallon and using a gasoline price of $2.27 per gallon, the five-year cost to power the vehicle is $4,864 ((60,000 miles / 28 miles per gallon) x $2.27 per gallon). This amount was rounded up to $5,000 for the traditional (gas) model, and the estimated five-year cost to power the hybrid model ($3,500) was reported as 70 percent (a reflection of the relationship between fuel efficiencies of the two models, 28 mpg / 40 mpg = 70%) of the cost of powering the traditional model.

The undiscounted total cost of the traditional model is $30,440: the $24,000 purchase price, plus $1,440 sales tax, plus $5,000 five-year fuel cost. The undiscounted total cost of the hybrid model is $30,450: the $27,500 purchase price, plus $1,650 sales tax, plus $3,500 five-year fuel cost, minus $2,200 tax savings for purchasing the hybrid. The difference of $10 in undiscounted total cost is in favor of the traditional model, but this amount is assumed to be immaterial.

After reading the introductory information on the friend’s purchase decision, participants were informed that the friend may qualify for a federal tax incentive that could reduce the friend's federal income tax if the hybrid model is purchased. Participants were also informed that the burden of determining eligibility to take advantage of the federal tax incentive falls on the taxpayer (the friend, with the help of the participant), and were provided with a list of eligibility requirements to consider. After receiving the list of eligibility requirements, participants were provided with the detailed list of specifications for each vehicle mentioned on an earlier screen. After reviewing the eligibility requirements and the specifications, participants received information regarding the structure (credit or deduction) of the incentive as well as detailed tax calculations specific to each vehicle purchase alternative. This process is illustrated in detail in Figure 2, and the full instrument is provided in the Appendix.

Figure 2

Detailed Progression of Experimental Instrument

Introduction

Participants assume role of advisor to a friend making vehicle purchase decision

Participants view basic information on each of two comparable and acceptable models identified by the friend – a traditional (gas) model and a hybrid model

Tax Incentive Eligibility

Participants learn of availability of a federal income tax incentive for hybrid model purchases

Participants view list of eligibility requirements friend must meet to be eligible for the tax incentive (manipulated – high complexity or low complexity)

Participants view detailed list of specifications for each model

Tax Incentive Structure

Participants informed of structure of tax incentive (manipulated – tax credit or tax deduction)

Participants view information on friend's estimated tax position given no vehicle purchase, the purchase of the traditional (gas) model, and the purchase of the hybrid model

Dependent Variable

Participants provide a recommendation (DV) to the friend using an 11-point sliding scale:
0 = definitely recommend traditional (gas) model, 10 = definitely recommend hybrid model

Conclusion

Participants provide answers to various follow-up questions

Participants provide answers to various demographic questions

Participants conclude work in instrument and request payment

Independent Variables

I manipulated my two independent variables, incentive structure (credit vs. deduction) and eligibility determination complexity (low complexity vs. high complexity), between participants to form four treatment groups. In the low (high) eligibility determination complexity condition, participants were presented with a list of two (eight) requirements that a taxpayer must meet to be eligible to take advantage of the tax incentive. While the actual determination of the friend's eligibility was not explicitly required, the fact that the purchase of the hybrid vehicle presented in the experiment was indeed eligible for the incentive was held constant across treatment conditions.

In the credit (deduction) incentive structure condition, participants were told that the tax incentive comes in the form of a tax credit (tax deduction) and a calculation of the friend's estimated income tax situation before and after considering the incentive was provided.[9] While they are different, deductions for adjusted gross income (or "above-the-line deductions) and deductions from adjusted gross income (the greater of the standard deduction or the sum of itemized deductions) affect taxable income and tax due in the same manner (see Figure 1 above). So, all participants viewed tax calculations incorporating a $12,000 standard deduction (deductions from adjusted gross income are held constant across conditions), and participants in treatment groups featuring the deduction structure saw the tax incentive delivered as a deduction for adjusted gross income. And, although the structure of the incentive varied by treatment condition, the tax effect or economic value of the incentive ($2,200 decrease in tax) was held constant across conditions.

[9] By calculating the tax effects of the incentive and providing it to participants instead of asking participants to calculate the tax effects on their own, calculation complexity is effectively held constant.

Dependent Variable

The dependent variable of interest for my study, *Recommendation*, closely parallels the dependent variable of interest from Morrow and Rupert (2015), which measured participant model preference for a personal car purchase decision using a seven-point Likert scale. In the current study, I ask participants to indicate their recommendation to the friend that requested advice on an eleven-point sliding scale (with numbers omitted from the scale), ranging from "would definitely recommend the traditional (gas) model" to "would definitely recommend the hybrid model." I use an unnumbered scale to avoid potential bias related to choosing certain numbers and because the numbers have no meaning beyond their coding for statistical analysis.

After providing a recommendation and without the ability to go back to change the response, I asked participants in all conditions to indicate whether they would have liked to have had additional information (yes or no) when making the decision. An open-ended question followed to allow participants to indicate specific information they would have found to be useful. After providing responses to manipulation and attention check questions (discussed below), participants were asked to provide responses to several questions aimed at understanding recommendations and several questions aimed at understanding preferences for tax incentive structures. Participants were also asked to provide answers to various demographic questions.

Participants

Participants were recruited through the Amazon Mechanical Turk platform. I used the third-party service of CloudResearch, powered by TurkPrime (formerly known as TurkPrime) to handle posting, payments, and other administrative tasks related to the study (Litman, Robinson, and Abberbock 2017). The use of this data source allowed me to recruit the most appropriate sample for this study – a sample that represents US taxpayers and features appropriate variability in taxpayer experience, which would likely not have been attained by recruiting university students.[10] Multiple studies have recently provided evidence that samples obtained through Amazon Mechanical Turk are appropriate for use in academic research. For example, Farrell, Grenier, and Leiby (2017) used a three-experiment approach, finding evidence that "online workers are willing to report their private information honestly and to exert effort, even when these choices are very costly" (94). Also, Buchheit, Doxey, Pollard, and Stinson (2018) conclude that "MTurk participants are reasonable proxies for nonprofessional subjects with limited exceptions (e.g., non-U.S. MTurk participants may be cause for concern)" (119).

The Qualtrics instrument was accessed 1,174 times through Amazon Mechanical Turk. An early screening question ("How many years have you filed a federal income tax return for yourself / your family?") led to immediate screen-outs of 327 participants answering "0 to 5 years". Fifty unique Amazon Mechanical Turk Worker IDs were rejected payment for various reasons.[11] Many of these 50 rejected workers logged multiple attempts, leading to a total reduction of 97 observations. In addition to screen-outs and rejected payments, total observations was also reduced by three for participants failing to request payment. The full final sample included 747 observations for unique Amazon Mechanical Turk Worker IDs receiving payment (see Table 1 below).

[10] I used several screening tools in Amazon Mechanical Turk: age ≥ 18, US citizen, US location at time of participation (with blocking of suspicious geocode locations), 90 – 100 percent approval rate for Amazon Mechanical Turk Human Intelligence Tasks (HITs), less than 500 HITs approved, blocking of duplicate IP addresses

[11] The most common reason for a payment rejection was the case of participants first accessing the instrument and answering the screening question in a manner leading to a screen-out. The same Amazon Mechanical Turk Worker ID was later recorded on a subsequent attempt with the screening question answer changed to avoid screen-out. Other reasons for rejection of payment included invalid Worker IDs entered in Qualtrics and invalid secret codes entered for payment.

Table 1

Sample Construction

Times instrument accessed through Amazon Mechanical Turk	1,174
Less: Immediate screen-outs for low tax return experience[1]	(327)
Less: Observations eliminated due to rejected payments[2]	(97)
Less: Observations eliminated due to no payment request[3]	(3)
Final Sample	747

Notes:
[1]Participants responding "0 to 5 years" to the question of "How many years have you filed a federal income tax return for yourself / your family?" were screened out without pay before accessing the full instrument.
[2]Payment was rejected for various reasons for 50 unique Amazon Mechanical Turk Worker IDs. Many of these 50 IDs logged multiple attempts to access the instrument (a reason for payment rejection) such that eliminating these participants eliminated 97 observations.
[3]Three participants logged complete attempts but never requested payment for their participation.

Participants included in the full final sample were 36.14 years old on average, and approximately 66 percent indicated household income less than $75,000. Approximately 58 percent of participants indicated tax return experience of fifteen years or less. Approximately half of the participants indicated experience filing tax returns that included deductions for AGI, itemized deductions, and tax credits (approximately 52, 47, and 56 percent, respectively). All participants providing complete responses and properly requesting payment through Amazon Mechanical Turk were paid a flat fee of $2.00 for their participation, which required, on average, 10.02 minutes of their time (an hourly wage of approximately $12 per hour). My sample includes participants who are slightly younger than those in the Morrow and Rupert (2015) sample (63.9 percent of their sample was over the age of 45). The distribution of participants across genders in my study (58.77 percent female) is approximately equal to the distribution in the Morrow and Rupert (2015) study (56.4 percent female). See Table 2 below for a full listing of descriptive statistics for the full sample.

Table 2

Descriptive Statistics of Demographic Variables

Age (Full Sample, n = 747)		
Mean		36.14
Standard Deviation		10.11

Full Sample Percentages

	n	%
Gender[1]		
Male	306	40.96
Female	439	58.77
Household Income		
$0 - $24,999	76	10.17
$25,000 - $49,999	228	30.52
$50,000 - $74,999	190	25.44
$75,000 - $99,999	109	14.59
> $100,000	144	19.28
Tax Return Experience		
6 to 10 years	250	33.47
11 to 15 years	182	24.37
16 to 20 years	107	14.32
More than 20 years	208	27.84
Filed Return with Deduction for AGI		
Yes	389	52.08
No	358	47.92
Filed Return with Itemized Deductions		
Yes	351	46.99
No	396	53.01
Filed Return with Tax Credits		
Yes	421	56.36
No	326	43.64

Table 2 (continued)

	n	%
Purchased Hybrid or Electric Vehicle in Past		
Yes	71	9.50
No	676	90.50
Currently Shopping for New Vehicle		
Yes	242	32.40
No	505	67.60

Notes:
[1]Two participants selected “prefer not to answer when responding to a gender demographic question.

IV. ANALYSIS OF RESULTS

Manipulation Checks

To verify the appropriateness of the manipulations of incentive structure and eligibility determination complexity, participants were asked several questions after providing their recommendations (the dependent variable). Participants first indicated on an eleven-point sliding scale the level of complexity involved in determining eligibility for the tax incentive, ranging from (0) not at all complex to (10) extremely complex. The mean value (standard deviation) indicated by participants randomly assigned to the two groups featuring low eligibility determination complexity was approximately 3.63 (2.68), while that of the participants in the two high eligibility determination complexity groups was approximately 4.25 (2.64). This difference, which is statistically significant ($p = .001$, two-tailed), indicates that participants in the high complexity groups did indeed find the eligibility determination requirements to be more complex than those encountered by participants in the low complexity groups.

Additionally, participants were asked to provide an assessment of the level of complexity involved in determining the actual tax effect the tax credit / tax deduction had on the friend's tax liability, ranging from (0) not at all complex to (10) extremely complex. A significant difference here would be surprising as participants in all groups were provided with the actual calculation of the tax effect of the incentive. The mean value (standard deviation) indicated by participants randomly assigned to the two groups featuring a credit structure was approximately 3.98 (2.58), while that of the participants in the two deduction structure groups was approximately 4.12 (2.57). This difference is not statistically significant ($p = .471$, two-tailed), providing evidence that calculation complexity differences between the credit and deduction structures was effectively controlled for and not likely to influence results.

The results above are consistent with differences (or lack thereof) in the amount of time participants spent in the task. Participants assigned to groups featuring high eligibility determination complexity spent significantly more time in the task than those in groups with low complexity (means of 10.48 and 9.56 minutes, respectively; $p = .034$, two-tailed). However, the amount of time spent in the task by participants responding to a credit structure (mean = 9.95 minutes) did not significantly differ ($p = .745$, two-tailed) from the amount of time spent in the task by those responding to a deduction structure (mean = 10.09 minutes).

Attention Checks

Several additional questions were used to verify participants devoted ample attention to the task. These six items included task-specific questions and, following guidance from Buchheit et al. (2018), a question confirming participant understanding of the flat fee payment structure. The results of three of these questions provided general evidence of satisfactory "basic" attention – most participants correctly answered questions regarding the most expensive option (approx. 93% answered correctly), the option with the highest five-year fuel cost (approx. 95% answered correctly), and the structure of the payment for participation (approx. 97% answered correctly). Three other questions assessed participant understanding of more "advanced" features of the task environment. Approximately 80.5 percent of participants correctly answered a question regarding the friend's eligibility status for the tax incentive, approximately 64 percent correctly identified the structure of the tax incentive (credit or deduction) encountered in the task, and approximately 74.2 percent correctly identified the actual tax effect ($2,200 reduction in taxes) of the incentive encountered in the task. The accuracy of answers provided for the actual tax effect question, however, varied markedly between groups assigned to credit (approx. 88.9% answered correctly) vs. deduction (approx. 59.6% answered correctly) conditions. This difference leads to noticeable differences in sample size in subsamples constructed below. The mean number of attention check questions answered correctly out of six was approximately 5.04.

I used the results of these attention check questions to construct multiple subsamples of interest. I constructed subsamples including participants correctly answering all six attention check questions (approx. 38.3% of the full sample, hereafter referred to as the "full attention" subsample), participants correctly answering the three "advanced" attention check questions (approx. 43.4% of the full sample, hereafter referred to as the "advanced attention" subsample), participants correctly answering at least five of the six (that is, **any** five of the six) attention check questions (approx. 75.2% of the full sample, hereafter referred to as the "high attention" subsample), and participants correctly answering the three "basic" attention check questions identified above (approx. 87.1% of the full sample, hereafter referred to as the "basic attention" subsample).

Dependent Variable

The full sample mean (grand mean) of my dependent variable, *Recommendation*, was 8.21 (see Table 3 below). This measure represents a strong preference among participants for the hybrid model, as responses were indicated on an eleven-point sliding scale (numbers omitted) ranging from "would definitely recommend the traditional (gas) model" (0) to "would definitely recommend the hybrid model" (10). The strong preference is likely not attributable to sampling people who already own hybrid vehicles – recall from Table 1 above that only 9.5 percent of the full sample indicated they have purchased a hybrid or electric vehicle in the past. This preference for the hybrid model is consistent with the results of the study by Morrow and Rupert (2015), which also found a general preference in favor of a hybrid model over a traditional (gas) model. This preference, however, is stronger in my study, which can likely be attributed, at least in part, to my design choice to hold constant the after-tax cost of each model.

Table 3

Descriptive Statistics for *Recommendation* – Full Sample

		Eligibility Determination Complexity		
		Low	*High*	Total
Incentive Structure	*Credit*	8.326 (2.352)	7.867 (2.810)	8.102 (2.592)
	Deduction	8.348 (2.153)	8.286 (2.232)	8.316 (2.190)
	Total	8.337 (2.253)	8.081 (2.536)	8.210 (2.399)

Variable Definitions:

Recommendation: participants responded to "Considering the information presented on your friend's vehicle purchase alternatives, please indicate your recommendation using the following scale:" using an 11-point sliding scale ranging from 0 ("would definitely recommend the traditional (gas) model") to 10 ("would definitely recommend the hybrid model")

Eligibility Determination Complexity (*EligCondition*): participants were randomly assigned to a group featuring a tax incentive with low (2 factors to consider) or high (8 factors to consider) eligibility determination complexity

Incentive Structure (*IncStructureCondition*): participants were randomly assigned to a group featuring a tax incentive structured as a credit or a deduction

Control Variables

I identified several potentially important control variables before conducting the experiment. Morrow and Rupert (2015) and Morrow et al. (2018) include gender as a control variable in their analyses, and the prior includes measures of participants' concern for the environment and participants' views on tax system complexity, so careful examination of differences related to these three variables is warranted in my study. Additionally, because Morrow et al. (2018) provides evidence that young, inexperienced taxpayers may have different structure preferences than older, more experienced taxpayers, careful examination of differences related to age and tax return experience is also warranted. Upon evaluation of correlations between variables collected, however, I found no evidence of significant correlation between the dependent variable and age or tax return experience.

Dependent variable scores did not significantly vary by gender when I considered the full sample (means of 8.32 and 8.06 for females and males, respectively). In fact, scores did not significantly vary by gender when I considered any of the subsamples constructed by attention check performance. However, mean dependent variable scores **did** vary significantly by gender when I considered subsamples that captured the balance of participants omitted in the subsamples constructed by attention check performance. For example, in a subsample constructed to exclusively include participants **not** correctly answering at least five attention check questions (the balance of the participants not included in the "high attention" subsample), female participants provided a significantly stronger *Recommendation* in favor of the hybrid model than male participants (means of 7.94 and 7.04, respectively; $p = .033$, two-tailed). There was not a significant difference in mean *Recommendation* scores by gender for the corresponding "high attention" subsample (means of 8.44 and 8.40 for females and males, respectively). This trend is robust across the "full attention" and "advanced attention" subsamples. Among participants indicating some lack of attention to or understanding of the tax decision context, perhaps those making their decisions based largely on emotion, it appears that female participants illustrate a stronger preference for the hybrid model than male participants. I examine this finding more closely below.

There was evidence of a significant positive correlation between the dependent variable and participant concern for the environment (*Pollution*) – preference for the hybrid model increases as concern for the environment increases. Two other variables were significantly correlated with the dependent variable at the 0.05 level. First, participant view of tax system complexity (*System_Complex*) was negatively correlated with *Recommendation* – preference for the hybrid model decreases as the feeling that the tax system is too complex increases. Secondly, awareness of the actual tax incentive that exists in the current IRC for the purchase of hybrid vehicles (*Aware*) was positively correlated with *Recommendation* – preference for the hybrid model increases as awareness of the actual tax incentive in the current IRC increases. The *System_Complex* and *Aware* variables, however, were significantly correlated with each other, so only the *Pollution* and *System_Complex* variables were included as covariates in the analysis of covariance (ANCOVA) models that follow. Table 4 below reports correlation coefficients for selected variables.

Table 4

Correlation Coefficients for Selected Variables

	Rec	Male	Age	Pollute	Comp	Aware	D_AGI	D_Item	Credit	TRExp	Income	HybEle	Shop
Rec		-.054	-.001	.345***	-.114***	.090**	.005	.001	.065	-.040	-.037	.006	-.034
Male	-.029		-.128***	-.009	.037	.097***	.031	.007	-.090**	-.077**	.065	.092**	.057
Age	-.029	-.099***		-.054	.161***	-.066	.127***	.225***	.068	.687***	.028	.016	-.150***
Pollute	.343***	.001	-.058		-.042	.049	-.049	-.046	-.026	-.058	-.034	.016	.039
Comp	-.092**	.055	.162***	.018		-.089**	-.018	.060	-.058	.145***	.050	-.004	-.033
Aware	.082**	.099***	-.069	.054	-.079**		.041	.041	-.016	-.090**	-.029	.151***	.085**
D_AGI	.012	.031	.145***	-.054	-.014	.041		.270***	.215***	.130***	.081**	.064	-.040
D_Item	-.020	.007	.226***	-.050	.067	.042	.270***		.125***	.179***	.137***	.079**	.025
Credit	.066	-.090**	.107***	-.036	-.051	-.016	.215***	.125***		.074**	-.038	<.001	-.020
TRExp	-.053	-.077**	.744***	-.057	.156***	-.085**	.130***	.179***	.074**		.088**	.010	-.157***
Income	-.046	.065	.078**	-.028	.058	-.027	.081**	.137***	-.038	.088**		.019	-.036
HybEle	.007	.092**	.025	.022	-.005	.155***	.064	.079**	<.001	.010	.019		-.088**
Shop	-.015	.057	-.133***	.054	-.030	.080**	-.040	.025	-.020	-.157***	-.036	-.088**	

Notes: Table 2 presents Pearson correlation coefficients above the diagonal and Spearman correlation coefficients below the diagonal for selected variables. ** and *** indicate significance (two-tailed) at the .05 and .01 levels, respectively.

Variable Definitions:

Recommendation ("Rec"): participants responded to "Considering the information presented on your friend's vehicle purchase alternatives, please indicate your recommendation using the following scale:" using an 11-point sliding scale ranging from 0 ("would definitely recommend the traditional (gas) model") to 10 ("would definitely recommend the hybrid model")

Male: a dichotomous variable indicating gender as male (1) or female (0)

Table 4 (continued)

Age: participant age in years

Pollution ("Pollute"): participants responded to "I believe that vehicle-related pollution is harmful to the environment and reducing this pollution is important to me" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly agree")

System_Complex ("Comp"): participants responded to "I believe that the federal tax system in the United States is too complex" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly disagree")

Aware: participants responded to "I am aware of the actual federal tax incentive that exists for hybrid vehicle purchases and this knowledge influenced by recommendation" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly disagree")

D_AGI: a dichotomous variable indicating that the participant has (1) or has not (0) filed a tax return in the past that included a deduction for AGI

D_Item: a dichotomous variable indicating that the participant has (1) or has not (0) filed a tax return in the past that included itemized deductions

Credit: a dichotomous variable indicating that the participant has (1) or has not (0) filed a tax return in the apst that included a tax credit

TRExp: a dichotomous variable indicating that the participant has tax return experience of more than 15 years (1) or tax return experience of 15 years or less (0)

Income: a dichotomous variable indicating that the participant has household income of $75,000 or more (1) or household income of less than $75,000 (0)

HybEle: a dichotomous variable indicating that the participant has (1) or has not (0) purchased a hybrid or electric vehicle in the past

Shop: a dichotomous variable indicating that the participant is (1) or is not (0) currently shopping for a new personal vehicle

Tests of Hypotheses and Consideration of Research Question

First, I focus on results related to participants demonstrating a high level of attention through performance on the six attention check questions detailed above, specifically presenting results from the "high attention" subsample. Recall that the "high attention" subsample was constructed to only include participants correctly answering at least five of the six (any five of the six) attention check questions. I found qualitatively similar results for the "full attention" (constructed to only include participants correctly answering all attention check questions) and "basic attention" (constructed to only include participants correctly answering the three most basic attention check questions) subsamples, so I do not separately present these results below. Dependent variable unadjusted means with standard deviations and adjusted means with standard errors for the "high attention" subsample are reported by treatment group in Panel A of Table 5 below. I estimated an ANCOVA model to assess the effects of eligibility determination complexity and incentive structure on the dependent variable. The covariates identified above (*Pollution* and *System_Complex*) were also included in the model.

I predict in H1 that individuals will be more (less) likely to engage in a tax-incentivized behavior when the process of determining eligibility for the incentive is less (more) complex. The results of the ANCOVA reported in Panel B of Table 5 provide support for H1. The *EligCondition* variable is a significant predictor of *Recommendation* ($F = 4.173$, $p = .042$, two-tailed) in the estimated ANCOVA model. The mean values in Panel A of Table 5 indicate that participants in groups featuring low eligibility determination complexity issued a stronger *Recommendation* in favor of the tax-incentivized hybrid model of the vehicle. There is also evidence of a significant main effect of eligibility determination complexity in the "full attention" and "basic attention" subsamples (not reported). Complexity in determining eligibility for a tax incentive encouraging the purchase of hybrid vehicles, it appears, has a behavioral effect consistent with that found in the EITC study by Bhargava and Manoli (2015). The hassle cost of eligibility determination complexity affects taxpayers responding to incentives encouraging the use of discretionary income in a similar manner to its effect on taxpayers deciding whether to participate in means-tested aid programs.

I predict in H2 that individuals will be more (less) likely to engage in a tax-incentivized behavior when the tax incentive is structured as a tax credit (tax deduction). I do not find support for this hypothesized main effect - the *IncStructureCondition* variable is not a significant predictor of *Recommendation* ($F = .338$, $p = .561$, two-tailed) in the estimated ANCOVA model. This finding is robust as I find no evidence to support a main effect of tax incentive structure in any of the subsamples considered. This lack of support for H2 suggests that taxpayer behavior is not differentially affected by different tax incentive structures *alone*. This finding suggests that taxpayers seem to be rational in their consideration of tax incentives – given an equal tax effect there is no evidence of a general preference for one structure over the other.

Table 5

Analysis of *Recommendation* for "High Attention" Subsample[1]

Panel A: *Recommendation* Descriptive Statistics

	Unadjusted		Adjusted		n
Group[2]	**Mean**	**Std. Dev.**	**Mean**	**Std. Error**	
Low / Credit	8.649	1.898	8.648	.168	148
Low / Deduction	8.661	1.647	8.559	.184	124
High / Credit	8.034	2.815	8.104	.169	147
High / Deduction	8.378	2.109	8.395	.172	143

Panel B: ANCOVA Results for *Recommendation*

Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**[4]	
Pollution[3]	310.689	1	310.689	74.406	<.001	***
System_Complex[3]	13.262	1	13.262	3.176	.075	*
EligCondition	17.425	1	17.425	4.173	.042	**
IncStructureCondition	1.410	1	1.410	.338	.561	
EligCondition*IncStructureCondition	5.043	1	5.043	1.208	.272	
Error	2321.621	556	4.176			

Notes:

[1]The table presents unadjusted and adjusted descriptives and the results of an analysis of covariance for a subsample constructed to exclusively include participants correctly answering at least five of six attention check questions.

[2]Group: participants were randomly assigned to four treatment groups featuring combinations of eligibility determination complexity and tax incentive structure - "Low" / "High" = low / high eligibility determination complexity, "Credit" / "Deduction" = credit / deduction tax incentive structure

[3]Adjusted means calculated with the following covariate values: *Pollution* = 7.70 and *System_Complex* = 6.98.

[4]*,**,*** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. All reported p-values are two-tailed.

Table 5 (continued)

Variable Definitions:

Recommendation: participants responded to "Considering the information presented on your friend's vehicle purchase alternatives, please indicate your recommendation using the following scale:" using an 11-point sliding scale ranging from 0 ("would definitely recommend the traditional (gas) model") to 10 ("would definitely recommend the hybrid model")

EligCondition: participants were randomly assigned to a group featuring a tax incentive with low (2 factors to consider) or high (8 factors to consider) eligibility determination complexity

IncStructureCondition: participants were randomly assigned to a group featuring a tax incentive structured as a credit or a deduction

Pollution: (a covariate) participants responded to "I believe that vehicle-related pollution is harmful to the environment and reducing this pollution is important to me" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly agree")

System_Complex: (a covariate) participants responded to "I believe that the federal tax system in the United States is too complex" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly disagree")

Although I did not find evidence to support a main effect of tax incentive structure, it is possible that tax incentive structure can affect taxpayer behavior through interactions with other variables. I also explored, as a research question, whether the effect of eligibility determination complexity (*EligCondition*) on the dependent variable (*Recommendation*) depends on the tax incentive's structure (*IncStructureCondition*). Although not robust across the subsamples of interest, there is some evidence of a significant interaction. The interaction term included in the ANCOVA model for the subsample constructed to exclusively include participants correctly answering all of the "advanced" attention check questions (questions on eligibility status, incentive structure, and the incentive's actual tax effect) is significant at the 0.10 level ($F = 2.934$, $p = .088$, two-tailed). Mean *Recommendation* scores and the results of the ANCOVA for the "advanced attention" subsample are presented below in Table 6, Panel A and Panel B, respectively.

These results suggest that the effect of a tax incentive's eligibility determination complexity depends on the tax incentive's structure. A post hoc analysis of simple effects, as shown below in Table 6, Panel C, indicates that the effect of eligibility determination complexity is significant in the credit structure ($F = 6.132$, $p = .014$, two-tailed, Bonferroni adjustment for multiple comparisons), but not significant in the deduction structure ($F = 0.023$, $p = .879$, two-tailed, Bonferroni adjustment for multiple comparisons). Within the credit structure, a shift from low to high eligibility determination complexity leads to a shift in *Recommendation* score adjusted means from 8.82 to 8.08 – a significant shift away from the incentivized hybrid model. Within the deduction structure, a shift from low to high eligibility determination complexity leads to a shift in *Recommendation* score adjusted means from 8.68 to 8.73 – a shift in the direction of the incentivized hybrid model that is not significant. These adjusted means are plotted below in Figure 3.

Table 6

Analysis of *Recommendation* for "Advanced Attention" Subsample[1]

Panel A: *Recommendation* Descriptive Statistics

Group[2]	**Unadjusted** Mean	**Unadjusted** Std. Dev.	**Adjusted** Mean	**Adjusted** Std. Error	**N**
Low / Credit	8.816	1.865	8.820	.221	87
Low / Deduction	8.769	1.455	8.676	.256	65
High / Credit	8.020	2.853	8.075	.205	102
High / Deduction	8.729	1.809	8.730	.248	70

Panel B: ANCOVA Results for *Recommendation*

Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**[4]	
Pollution[3]	106.977	1	106.977	25.156	<.001	***
System_Complex[3]	18.796	1	18.796	4.420	.036	**
EligCondition	9.305	1	9.305	2.188	.140	
IncStructureCondition	5.061	1	5.061	1.190	.276	
EligCondition*IncStructureCondition	12.477	1	12.477	2.934	.088	*
Error	1352.288	318	4.252			

Panel C: Post Hoc Analysis of Simple Effects

Source	**df**	**Mean Square**	**F**	**Sig.**[4]	
Effect of Eligibility Determination Complexity given Credit	318	26.077	6.132	.014[5]	**
Effect of Eligibility Determination Complexity given Deduction	318	.098	.023	.879[5]	
Effect of Incentive Structure given Low Eligibility Complexity	318	.776	.183	.669[5]	
Effect of Incentive Structure given High Eligibility Complexity	318	17.560	4.129	.043[5]	**

Table 6 (continued)

Notes:

[1]The table presents unadjusted and adjusted descriptives and the results of an analysis of covariance for a subsample constructed to exclusively include participants correctly answering all three “advanced” attention check questions.

[2]Group: participants were randomly assigned to four treatment groups featuring combinations of eligibility determination complexity and tax incentive structure - “Low” / “High” = low / high eligibility determination complexity, “Credit” / “Deduction” = credit / deduction tax incentive structure

[3]Adjusted means calculated with the following covariate values: *Pollution* = 7.74 and *System_Complex* = 7.04.

[4]*,**,*** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. All reported p-values are two-tailed.

[5] All p-values reported for simple effects are based on pairwise comparisons of estimated marginal means, which reflect a Bonferroni adjustment for multiple comparisons.

Variable Definitions:

Recommendation: participants responded to “Considering the information presented on your friend’s vehicle purchase alternatives, please indicate your recommendation using the following scale:” using an 11-point sliding scale ranging from 0 (“would definitely recommend the traditional (gas) model”) to 10 (“would definitely recommend the hybrid model”)

EligCondition: participants were randomly assigned to a group featuring a tax incentive with low (2 factors to consider) or high (8 factors to consider) eligibility determination complexity

IncStructureCondition: participants were randomly assigned to a group featuring a tax incentive structured as a credit or a deduction

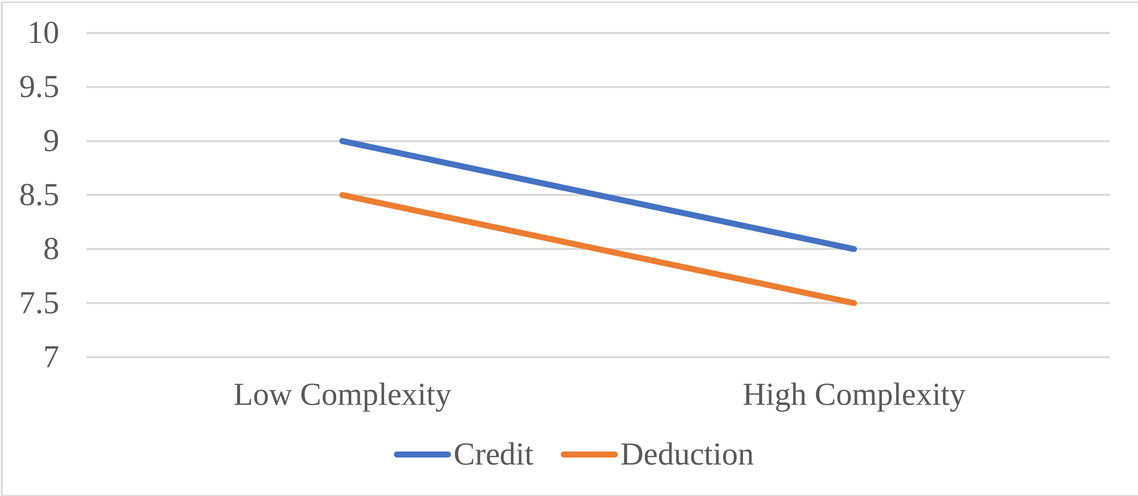
Pollution: (a covariate) participants responded to “I believe that vehicle-related pollution is harmful to the environment and reducing this pollution is important to me” using an 11-point sliding scale ranging from 0 (“strongly disagree”) to 10 (“strongly agree”)

System_Complex: (a covariate) participants responded to “I believe that the federal tax system in the United States is too complex” using an 11-point sliding scale ranging from 0 (“strongly disagree”) to 10 (“strongly disagree”)

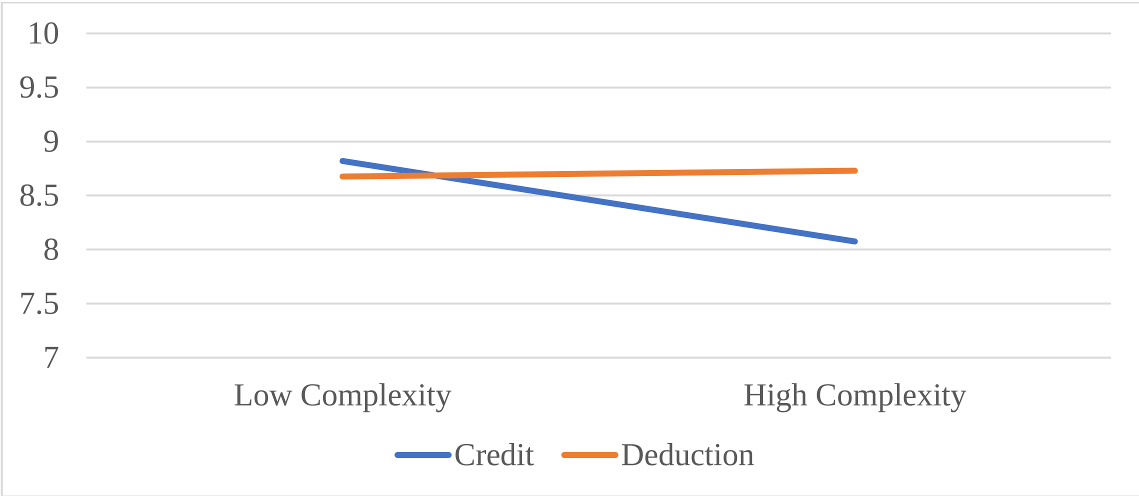
Figure 3

Effects of Eligibility Determination Complexity and Incentive Structure on *Recommendation* for the "Advanced Attention" Subsample

Panel A: Predicted Effects



Panel B: Actual Adjusted Means in the "Advanced Attention" Subsample[1]



Notes:
[1]The figure plots adjusted means for a subsample constructed to exclusively include participants correctly answering all three "advanced" attention check questions.

To this point, I have only considered subsamples constructed by attention check performance. It is possible, however, that the attention check questions used to create the subsamples analyzed above represent general tax return experience. The participants I recruited through Amazon Mechanical Turk represent a broad range of actual U.S. taxpayers. The participants correctly answering the various combinations of the attention check questions might represent a subset of the population of U.S. taxpayers most knowledgeable about and comfortable with our tax system. Similarly, it is possible that a different subset of actual U.S. taxpayers is not well-informed in the area of tax law and is appropriately represented by participants in my study that were unable to correctly answer attention check questions at a high rate. It is important, therefore, to consider broader subsamples and subsamples constructed using alternative construction approaches.

First, I consider the full sample of participants successfully completing the instrument and receiving payment ($n = 747$). Recall that the full sample mean of attention check questions answered correctly out of six was 5.04. When I estimate the same ANCOVA model for the full sample (two independent variables of interest, their interaction, and two covariates), I find results that are not entirely consistent with those detailed above for subsamples constructed by attention check performance. While there is still no evidence of a significant main effect of incentive structure ($F = .994$, $p = .319$, two-tailed), there is no evidence when analyzing the full sample of a significant main effect of eligibility determination complexity ($F = .691$, $p = .406$, two-tailed). Table 7 below presents unadjusted and adjusted means in Panel A and the results of the ANCOVA in Panel B.

Although the interaction term from the estimated ANCOVA model for the full sample is not considered significant ($F = 2.651$, $p = .104$, two-tailed) at traditional levels, it does warrant an analysis of simple effects. When considering these simple effects, I find evidence of a relationship consistent with that discussed above for the "advanced attention" subsample – the effect of eligibility determination complexity is significant at the 0.10 level in a credit structure ($F = 3.007$, $p = .083$, two-tailed, Bonferroni adjustment for multiple comparisons), but not significant in a deduction structure ($F = .317$, $p = .574$, Bonferroni adjustment for multiple comparisons). The shift from low to high eligibility determination complexity leads to a shift in adjusted means from 8.327 to 7.923 in the credit structure – a significant shift away from the incentivized hybrid model. The shift from low to high eligibility determination complexity leads to a shift in adjusted means from 8.224 to 8.354 in the deduction structure – a shift in the direction of the incentivized hybrid model that is not significant. These simple effects are presented below in Table 7, Panel C, and the adjusted means are plotted below in Figure 4, Panel A.

Table 7

Analysis of *Recommendation* for Full Sample[1]

Panel A: *Recommendation* Descriptive Statistics

Group[2]	Unadjusted Mean	Unadjusted Std. Dev.	Adjusted Mean	Adjusted Std. Error	n
Low / Credit	8.326	2.352	8.327	.163	190
Low / Deduction	8.348	2.153	8.224	.164	187
High / Credit	7.867	2.810	7.923	.167	181
High / Deduction	8.286	2.232	8.354	.163	189

Panel B: ANCOVA Results for *Recommendation*

Source	Type III Sum of Squares	df	Mean Square	F	Sig.[4]	
Pollution[3]	491.465	1	491.465	97.943	<.001	***
System_Complex[3]	42.409	1	42.409	8.452	.004	***
EligCondition	3.469	1	3.469	.691	.406	
IncStructureCondition	4.986	1	4.986	.994	.319	
EligCondition*IncStructureCondition	13.301	1	13.301	2.651	.104	
Error	3718.241	741	5.018			

Panel C: Post Hoc Analysis of Simple Effects

Source	df	Mean Square	F	Sig.[4]	
Effect of Eligibility Determination Complexity given Credit	741	15.090	3.007	.083[5]	*
Effect of Eligibility Determination Complexity given Deduction	741	1.590	.317	.574[5]	
Effect of Incentive Structure given Low Eligibility Complexity	741	.994	.198	.656[5]	
Effect of Incentive Structure given High Eligibility Complexity	741	17.176	3.423	.065[5]	*

Table 7 (continued)

Notes:
[1]The table presents unadjusted and adjusted descriptives and the results of an analysis of covariance for the full sample of 747 observations.
[2]Group: participants were randomly assigned to four treatment groups featuring combinations of eligibility determination complexity and tax incentive structure - "Low" / "High" = low / high eligibility determination complexity, "Credit" / "Deduction" = credit / deduction tax incentive structure
[3]Adjusted means calculated with the following covariate values: *Pollution* = 7.64 and *System_Complex* = 7.04.
[4]*,**,*** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. All reported p-values are two-tailed.
[5] All p-values reported for simple effects are based on pairwise comparisons of estimated marginal means, which reflect a Bonferroni adjustment for multiple comparisons.

Variable Definitions:
Recommendation: participants responded to "Considering the information presented on your friend's vehicle purchase alternatives, please indicate your recommendation using the following scale:" using an 11-point sliding scale ranging from 0 ("would definitely recommend the traditional (gas) model") to 10 ("would definitely recommend the hybrid model")
EligCondition: participants were randomly assigned to a group featuring a tax incentive with low (2 factors to consider) or high (8 factors to consider) eligibility determination complexity
IncStructureCondition: participants were randomly assigned to a group featuring a tax incentive structured as a credit or a deduction
Pollution: (a covariate) participants responded to "I believe that vehicle-related pollution is harmful to the environment and reducing this pollution is important to me" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly agree")
System_Complex: (a covariate) participants responded to "I believe that the federal tax system in the United States is too complex" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly disagree")

I used an approach similar to Morrow and Rupert (2015) to create an additional subsample. I split the full sample into deciles by amount of time spent in the task and eliminated observations for participants with times in the first and tenth deciles (hereafter referred to as the "middle eight deciles" subsample). While eliminating participants not devoting enough time to a task is a common approach (used in Morrow and Rupert 2015), the approach used here recognizes that too much time spent in the task also likely represents an attention problem (i.e., starting and stopping, frequent distractions, etc.). This subsample includes observations for 599 (out of 747) participants, and unadjusted and adjusted means for this subsample are reported in Panel A of Table 8 below.

I again estimated an ANCOVA model with the independent variables of interest, their interaction, and the *Pollution* and *System_Complex* covariates. The results of this ANCOVA (reported in Panel B of Table 8 below) are qualitatively similar to the results of the ANCOVA for the full sample reported in Table 7 above. Within the "middle eight deciles" subsample, there is no evidence of a main effect of eligibility determination complexity or incentive structure. The interaction of the two independent variables of interest, while again not considered significant at traditional levels ($p = .118$), is consistent with the results from the ANCOVA model estimated for the full sample. The adjusted means for the "middle eight deciles" subsample are plotted below in Figure 4, Panel B. Although the means (not reported) are slightly different, p-values (not reported) for the covariates, the independent variables, and the interaction term are qualitatively similar to and lead to the same conclusions when I consider a subsample constructed to only exclude participants spending less than five minutes in the task (the approach used in Morrow and Rupert 2015).

Table 8

Analysis of *Recommendation* for "Middle Eight Deciles" Subsample[1]

Panel A: *Recommendation* Descriptive Statistics

	Unadjusted		Adjusted		N
Group[2]	**Mean**	**Std. Dev.**	**Mean**	**Std. Error**	
Low / Credit	8.519	2.124	8.509	.169	156
Low / Deduction	8.345	2.131	8.292	.173	148
High / Credit	8.164	2.608	8.181	.182	134
High / Deduction	8.460	2.080	8.504	.166	161

Panel B: ANCOVA Results for *Recommendation*

Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**[4]	
Pollution[3]	312.229	1	312.229	70.760	<.001	***
System_Complex[3]	27.318	1	27..318	6.191	.013	**
EligCondition	.506	1	.506	.115	.735	
IncStructureCondition	.415	1	.415	.094	.759	
EligCondition*IncStructureCondition	10.821	1	10.821	2.452	.118	
Error	2616.606	593	4.412			

Panel C: Post Hoc Analysis of Simple Effects

Source	**df**	**Mean Square**	**F**	**Sig.**[4]
Effect of Eligibility Determination Complexity given Credit	593	7.724	1.750	.186[5]
Effect of Eligibility Determination Complexity given Deduction	593	3.440	.780	.378[5]
Effect of Incentive Structure given Low Eligibility Complexity	593	3.553	.805	.370[5]
Effect of Incentive Structure given High Eligibility Complexity	593	7.615	1.726	.189[5]

Table 8 (continued)

Notes:

[1]The table presents unadjusted and adjusted descriptives and the results of an analysis of covariance for a subsample constructed by separating the full sample into deciles by time spent in the task and eliminating the first and tenth deciles.

[2]Group: participants were randomly assigned to four treatment groups featuring combinations of eligibility determination complexity and tax incentive structure - “Low” / “High” = low / high eligibility determination complexity, “Credit” / “Deduction” = credit / deduction tax incentive structure

[3]Adjusted means calculated with the following covariate values: *Pollution* = 7.71 and *System_Complex* = 7.03.

[4]*,**,*** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. All reported p-values are two-tailed.

[5]All p-values reported for simple effects are based on pairwise comparisons of estimated marginal means, which reflect a Bonferroni adjustment for multiple comparisons.

Variable Definitions:

Recommendation: participants responded to “Considering the information presented on your friend’s vehicle purchase alternatives, please indicate your recommendation using the following scale:” using an 11-point sliding scale ranging from 0 (“would definitely recommend the traditional (gas) model”) to 10 (“would definitely recommend the hybrid model”)

EligCondition: participants were randomly assigned to a group featuring a tax incentive with low (2 factors to consider) or high (8 factors to consider) eligibility determination complexity

IncStructureCondition: participants were randomly assigned to a group featuring a tax incentive structured as a credit or a deduction

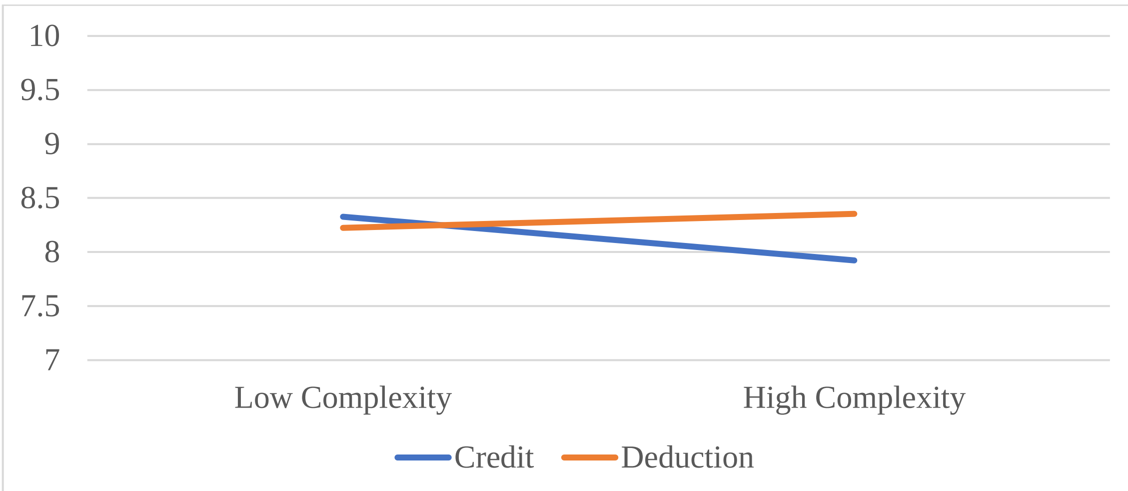
Pollution: (a covariate) participants responded to “I believe that vehicle-related pollution is harmful to the environment and reducing this pollution is important to me” using an 11-point sliding scale ranging from 0 (“strongly disagree”) to 10 (“strongly agree”)

System_Complex: (a covariate) participants responded to “I believe that the federal tax system in the United States is too complex” using an 11-point sliding scale ranging from 0 (“strongly disagree”) to 10 (“strongly disagree”)

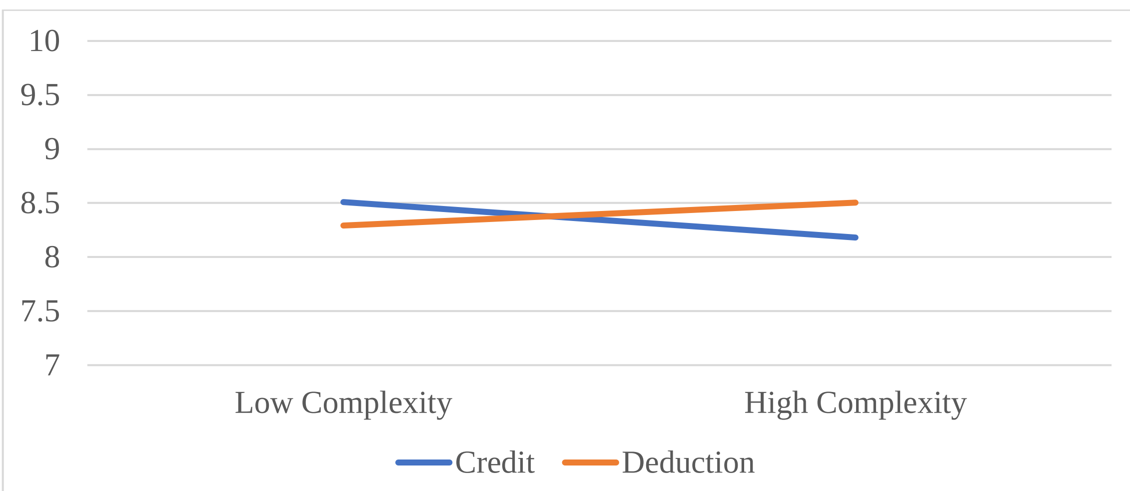
Figure 4

Effects of Eligibility Determination Complexity and Incentive Structure on *Recommendation* for the Full Sample and the "Middle Eight Deciles" Subsample[1]

Panel A: Actual Adjusted Means in the Full Sample



Panel B: Actual Adjusted Means in the "Middle Eight Deciles" Subsample[1]



Notes:
[1]The figure plots adjusted means for a subsample constructed by separating the full sample into deciles by time spent in the task and eliminating the first and tenth deciles.

The “middle eight deciles” subsample eliminates participants based on time spent in the task, but it does not explicitly account for attention check performance. I again considered the “middle eight deciles” subsample, but included an additional covariate to control for the effect of participant attention. The total number of attention check questions answered correctly (*AttnTotal*) was significantly correlated with *Recommendation* and was not significantly correlated with *Pollution* or *System_Complex*. I estimated an ANCOVA model including the two independent variables of interest, the two original covariates, and the *AttnTotal* covariate. I find results that are consistent with the ANCOVA models estimated for the full sample and the “middle eight deciles” subsample without the *AttnTotal* covariate – no significant main effects and a significant interaction ($F = 3.097$, $p = .079$, two-tailed). Unadjusted and adjusted descriptives and the results of the ANCOVA are reported in Table 9 below.

When considering simple effects (reported in Table 9, Panel C), I find more evidence to suggest that the effect of eligibility determination complexity is significant in the credit structure ($F = 2.822$, $p = .094$, two-tailed, Bonferroni correction for multiple comparisons), but not in the deduction structure ($F = .621$, $p = .431$, two-tailed, Bonferroni correction for multiple comparisons). Stated differently, I find that the effect of incentive structure is significant when a tax incentive has high eligibility determination complexity ($F = 3.786$, $p = .052$, two-tailed, Bonferroni correction for multiple comparisons), but not when eligibility determination complexity is low ($F = .258$, $p = .612$, two-tailed, Bonferroni correction for multiple comparisons). Within the credit structure, a shift from low to high eligibility determination complexity leads to a shift in *Recommendation* score adjusted means from 8.49 to 8.07 – a significant shift away from the incentivized hybrid model. Within the deduction structure, a shift from low to high eligibility determination complexity leads to a shift in *Recommendation* score adjusted means from 8.36 to 8.55 – a shift in the direction of the incentivized hybrid model that is not significant. These adjusted means are plotted below in Figure 5.

I find a recurring pattern when visually inspecting the means and standard deviations of *Recommendation* for all subsamples considered to this point. The means (unadjusted and adjusted) and standard deviations for three groups – the low eligibility complexity / credit group, the low eligibility complexity / deduction group, and the high eligibility complexity / deduction group – consistently form relatively tight clusters. The high eligibility complexity / credit group, however, is consistently different. This group features the lowest mean (unadjusted and adjusted) and the highest standard deviation across all subsamples considered to this point. This finding suggests that the results of a significant main effect of eligibility determination complexity and a significant interaction may be driven by this group.

Table 9

Analysis of *Recommendation* for "Middle Eight Deciles" Subsample with Attention Check[1]

Panel A: *Recommendation* Descriptive Statistics

	Unadjusted		**Adjusted**		**n**
Group[2]	**Mean**	**Std. Dev.**	**Mean**	**Std. Error**	
Low / Credit	8.519	2.124	8.486	.167	156
Low / Deduction	8.345	2.131	8.364	.171	148
High / Credit	8.164	2.608	8.073	.181	134
High / Deduction	8.460	2.080	8.550	.164	161

Panel B: ANCOVA Results for *Recommendation*

Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**[4]	
Pollution[3]	268.344	1	268.344	62.453	<.001	***
System_Complex[3]	25.001	1	25.001	5.819	.016	**
AttnTotal[3]	72.920	1	72.920	16.971	<.001	***
EligCondition	1.888	1	1.888	.439	.508	
IncStructureCondition	4.549	1	4.549	1.059	.304	
EligCondition*IncStructureCondition	13.307	1	13.307	3.097	.079	*
Error	2543.686	592	4.297			

Panel C: Post Hoc Analysis of Simple Effects

Source	**df**	**Mean Square**	**F**	**Sig.**[4]	
Effect of Eligibility Determination Complexity given Credit	592	12.124	2.822	.094[5]	*
Effect of Eligibility Determination Complexity given Deduction	592	2.670	.621	.431[5]	
Effect of Incentive Structure given Low Eligibility Complexity	592	1.108	.258	.612[5]	
Effect of Incentive Structure given High Eligibility Complexity	592	16.266	3.786	.052[5]	*

Table 9 (continued)

Notes:

[1]The table presents unadjusted and adjusted descriptives and the results of an analysis of covariance for a subsample constructed by separating the full sample into deciles by time spent in the task and eliminating the first and tenth deciles.

[2]Group: participants were randomly assigned to four treatment groups featuring combinations of eligibility determination complexity and tax incentive structure - "Low" / "High" = low / high eligibility determination complexity, "Credit" / "Deduction" = credit / deduction tax incentive structure

[3]Adjusted means calculated with the following covariate values: *Pollution* = 7.71, *System_Complex* = 7.03, and *AttnTotal* = 5.11.

[4]*,**,*** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. All reported p-values are two-tailed.

[5]All p-values reported for simple effects are based on pairwise comparisons of estimated marginal means, which reflect a Bonferroni adjustment for multiple comparisons.

Variable Definitions:

Recommendation: participants responded to "Considering the information presented on your friend's vehicle purchase alternatives, please indicate your recommendation using the following scale:" using an 11-point sliding scale ranging from 0 ("would definitely recommend the traditional (gas) model") to 10 ("would definitely recommend the hybrid model")

EligCondition: participants were randomly assigned to a group featuring a tax incentive with low (2 factors to consider) or high (8 factors to consider) eligibility determination complexity

IncStructureCondition: participants were randomly assigned to a group featuring a tax incentive structured as a credit or a deduction

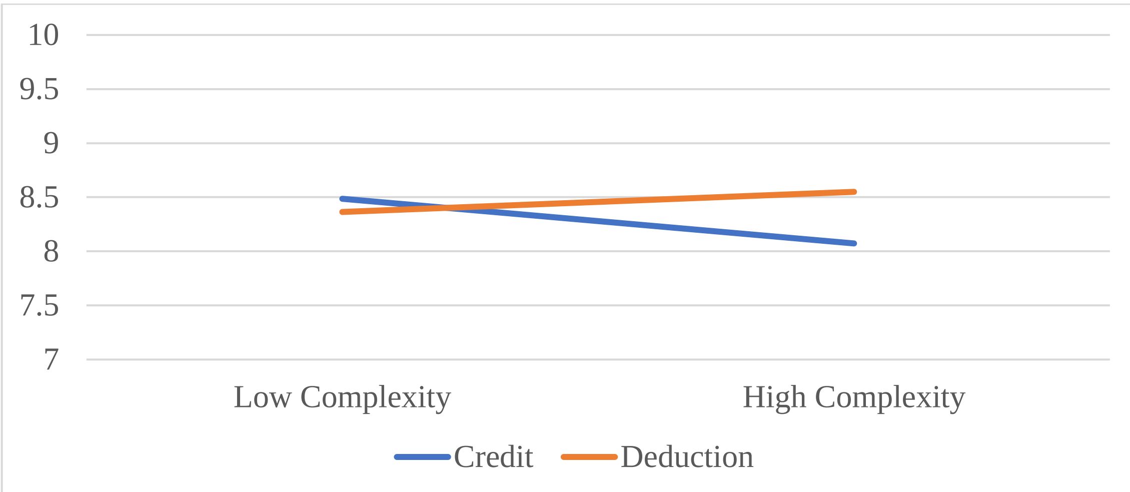
Pollution: (a covariate) participants responded to "I believe that vehicle-related pollution is harmful to the environment and reducing this pollution is important to me" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly agree")

System_Complex: (a covariate) participants responded to "I believe that the federal tax system in the United States is too complex" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly disagree")

AttnTotal: (a covariate) the total number of attention check questions (out of 6 total) answered correctly by the participant

Figure 5

Effects of Eligibility Determination Complexity and Incentive Structure on *Recommendation* for the "Middle Eight Deciles" Subsample[1] with Attention Check



Notes:
[1]The figure plots adjusted means for a subsample constructed by separating the full sample into deciles by time spent in the task and eliminating the first and tenth deciles.

General Linear Model Assumption Violations

ANCOVA relies on several assumptions common to general linear model analysis tools. Two of these assumptions – normal distribution of the errors (or Gaussian errors) and homogeneity of variance assumptions – are not satisfied in the data collected for this experiment. Figure 6 below shows the *Recommendation* dependent variable is negatively skewed due to a ceiling effect – a large number of participants (approximately 44% of participants in the full sample) chose the highest possible value (ten on a scale from zero to ten, strongly in favor of the hybrid model) when making their *Recommendation*. This type of departure from normality does not respond to data transformations (i.e., square root and log transformations). A common approach, given a sufficiently large sample size (the case in my study), is to ignore the assumption violations and rely on the robustness of the statistical test (ANCOVA in my study) to handle the violations.

I did, however, use an alternative approach to address the assumption violations. I dichotomized the dependent variable such that participants either did or did not make a *Recommendation* of ten out of ten (i.e., the dependent variable became ten or "not-ten"). I then estimated the following logistic regression model:

$$RecTen = \beta_0 + \beta_1 EligCondition\_Low + \beta_2 IncStructureCondition\_Credit + \beta_3 EligCondition\_Low * IncStructureCondition\_Credit + \beta_4\, Pollution + \beta_5 System\_Complex + \varepsilon.$$

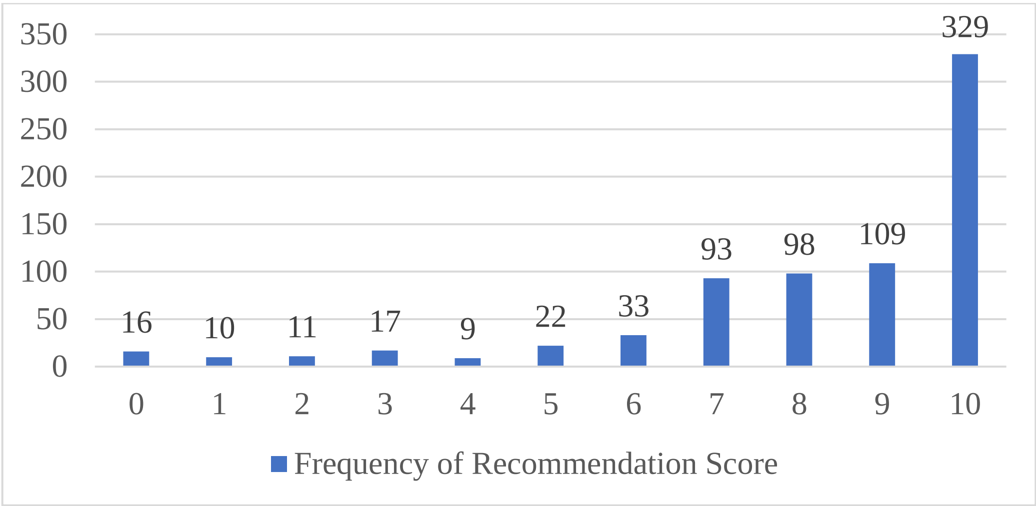
The dependent variable, *RecTen,* equals 1(0) for participants choosing (not choosing) the raw *Recommendation* score most strongly in favor of the hybrid model (a score of ten). The independent variable, *EligCondition_Low*, equals 1(0) if eligibility determination complexity is low (high), and the independent variable, *IncStructureCondition_Credit*, equals 1(0) if the incentive is structured as a credit (deduction). The *Pollution* and *System_Complex* variables are also included in the logistic regression model in the same form as indicated in the ANCOVA models above.

The results, however, revealed no significant relationships between the dichotomized dependent variable and the two independent variables of interest or their interaction. Further, when I drop the interaction term from the model, which shifts the interpretation of the independent variable coefficients from simple effects to main effects, I find no evidence of a significant relationship between the independent variables and the dichotomized *Recommendation* variable (not reported). Table 10 below reports the results of the logistic regression analysis for the full sample only, but the results of all subsamples are qualitatively similar.

Figure 6

Distribution of *Recommendation*

Panel A: Full Sample Distribution



Panel B: Distribution by Experimental Condition

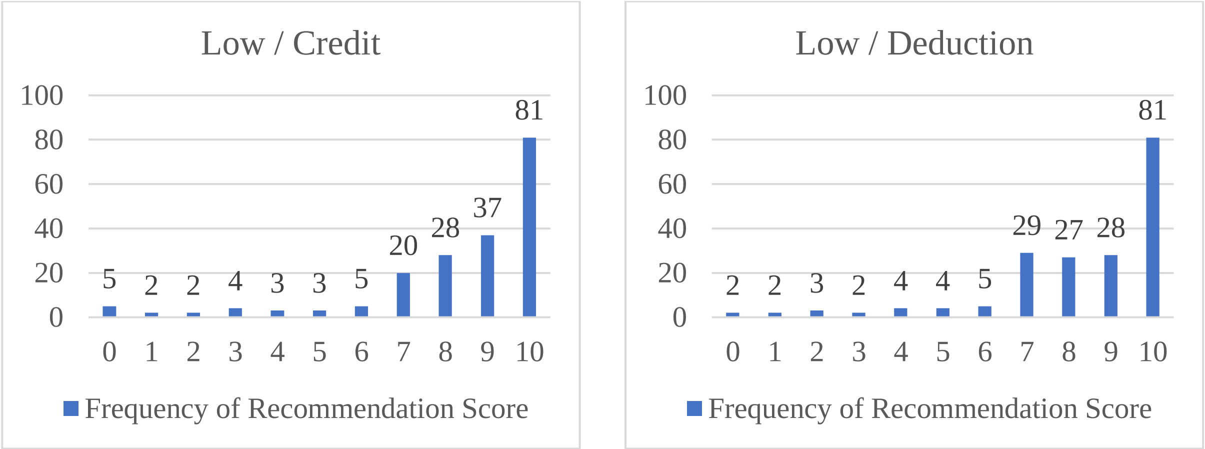
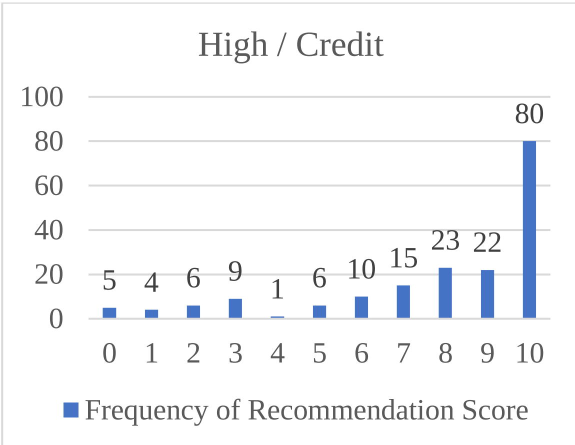


Figure 6 (continued)



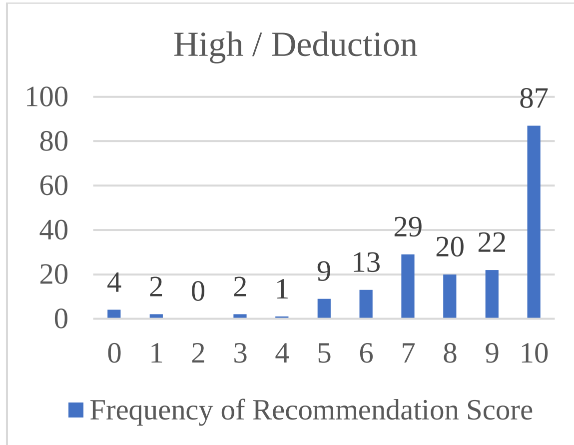


Table 10

Analysis of Likelihood of Strong Recommendation (*RecTen*) for Hybrid Model

Variable	β	Odds Ratio	S.E.	Wald Statistic	df	Sig.[2]	
Pollution	.276	1.318	.041	45.193	1	<.001	***
System_Complex	-.083	.920	.035	5.724	1	.017	**
EligCondition_Low	-.244	.784	.216	1.270	1	.260	
IncStructureCondition_Credit	-.083	.920	.218	.146	1	.703	
EligCondition_Low* IncStructureCondition_Credit	.133	1.142	.307	.188	1	.664	
Constant	-1.663	.190	.429	15.022	1	<.001	***

Model:

n = 747

χ^2 = 58.258***

Cox and Snell R^2 = .075

Notes:
[1]The table presents the results of a logistic regression analysis for the full sample.
[2]*,**,*** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. All reported p-values are two-tailed.

Variable Definitions:

RecTen: participants responded to “Considering the information presented on your friend’s vehicle purchase alternatives, please indicate your recommendation using the following scale:” using an 11-point sliding scale ranging from 0 (“would definitely recommend the traditional (gas) model”) to 10 (“would definitely recommend the hybrid model”) – coded as 1 if 10 and 0 if any score other than 10

EligCondition_Low: participants were randomly assigned to a group featuring a tax incentive with low (2 factors to consider) or high (8 factors to consider) eligibility determination complexity – coded as 1 if low and 0 if high

IncStructureCondition_Credit: participants were randomly assigned to a group featuring a tax incentive structured as a credit or a deduction – coded as 1 if credit and 0 if deduction

Pollution: (a covariate) participants responded to “I believe that vehicle-related pollution is harmful to the environment and reducing this pollution is important to me” using an 11-point sliding scale ranging from 0 (“strongly disagree”) to 10 (“strongly agree”)

System_Complex: (a covariate) participants responded to “I believe that the federal tax system in the United States is too complex” using an 11-point sliding scale ranging from 0 (“strongly disagree”) to 10 (“strongly disagree”)

This finding, however, can be explained to some extent through a close (visual) examination of the distributions for each of the experimental conditions shown above in Figure 6. As can be seen in Panel B, the frequencies of high scores (those strongly in favor of the hybrid model) are approximately equal across the experimental conditions and the sample sizes of the groups are also approximately equal. The independent variables are not significant in the logistic regression model above, at least in part, because there is little variation in the distribution of the dichotomized (ten vs. "not-ten") dependent variable across groups. The independent variables perform poorly in predicting scores of ten and "not-ten" because the variation in raw *Recommendation* scores occurs on the bottom half of the eleven-point scale (the half in favor of the traditional model).

I do find when looking at the distributions, however, a higher frequency of scores on the lower half of the eleven-point scale (scores 0 through 4) in the group that responded to a tax credit with high eligibility determination complexity. This finding is consistent with and provides an explanation for the inflated standard deviation values for this group compared to the other three groups as can be seen in Table 5, Table 6, Table 7, Table 8, and Table 9. It is also consistent with the ANCOVA results above that indicate a significant effect of eligibility determination complexity in the credit condition – participants in the high eligibility determination complexity / credit group more frequently made recommendations in favor of the traditional model (scores 0 through 4).

Supplemental Analysis: Open-Ended Questions

Participants provided responses to several follow-up questions after making their vehicle purchase recommendations. First, I used an open-ended question to ask participants to indicate the important factors that motivated their recommendations. Most comments indicated preference for the hybrid model, which is consistent with the full sample mean *Recommendation* score strongly in favor of the hybrid model. The participants that recommended against the hybrid often indicated they felt hybrid vehicles are too expensive to maintain. Many of the participants recommending in favor of the hybrid model cited lower fuel costs and lower environmental impact. Participants commonly indicated that the hybrid model was the "easy choice" because the tax incentive made it the same overall price as the traditional model – a clear indication of the effect of a tax incentive that effectively equalizes prices.

I used a second open-ended question to ask participants what additional information they would have preferred to have when making their recommendation. Some of the more common responses included the type / distance of normal driving for the friend, information regarding battery maintenance costs for the hybrid model, availability of public recharging stations, and a guarantee of eligibility for the incentive. This desire to see a guarantee of eligibility is an indication of the effect of eligibility determination complexity as some participants were apprehensive about recommending the hybrid model without perfect confidence regarding eligibility.

Supplemental Analysis: Certainty

Participants also answered a question regarding their level of certainty about how the incentive would affect their friend's tax liability. The level of certainty was indicated on an 11-point sliding scale ranging from 0 (not at all certain) to 10 (highly certain). In the full sample, the mean value of certainty indicated by participants in the credit structure groups was approximately 6.83, compared to a mean value of approximately 5.97 for participants in the deduction structure groups (a significant difference, $p = <0.001$). This finding is robust – mean values of certainty are significantly greater for participants responding to credits in all subsamples mentioned above. Further, the mean value of certainty does not significantly differ between low and high eligibility determination complexity in the full sample or any of the subsamples mentioned above. Because of the relationship with the marginal tax rate, credits have been deemed to entail more certainty than deductions for how much actual tax savings will accrue to a taxpayer when engaging in incentivized behavior and taking advantage of an incentive. This uncertainty, however, should have been effectively eliminated by design as the economic value of the incentive was held constant across incentive structure levels and the calculation of the tax effect was presented in the instrument.

This difference is especially interesting when considered alongside participant responses to other questions. As discussed above, responses to the manipulation check question regarding complexity in determining the incentive's actual tax effect were not significantly different between structure conditions. Three other follow-up questions aimed at uncovering a general taxpayer bias for one incentive structure over the other also failed to reveal strong preferences. Participants were asked to indicate on 11-point sliding scales (0 in favor of tax credit and 10 in favor of tax deduction) the structure they generally preferred (mean response approx. 4.94), the structure they found to be easiest to handle (mean response approx. 5.06), and the structure they found to be most valuable (mean response approx. 4.93). These seemingly-conflicting results suggest that average taxpayers are more comfortable dealing with tax incentives structured as credits, but are generally unaware of or unwilling to disclose their bias.

Supplemental Analysis: Gender

As indicated above, I found some evidence of differences by gender when considering subsamples constructed to exclusively include participants **not** correctly answering various combinations of attention check questions. Among all subsamples constructed by attention check performance, the "advanced attention" subsample provides the most even split of observations – 324 participants correctly answered all three advanced attention questions and 423 did not. Recall that the "advanced attention" subsample was constructed to only include participants correctly answering questions on the "advanced" features of the task environment (questions on eligibility status, incentive structure, and the incentive's actual tax effect). So, I split a subsample constructed to exclusively include participants **not** correctly answering the three "advanced" attention check questions by gender and estimated the same ANCOVA model from above for each new gender-specific subsample. Adjusted means and the results of the ANCOVAs are reported below in Table 11.

I find evidence of a significant interaction in the female-only subsample, but no evidence of an interaction in the male-only subsample. In fact, males and females **not** performing well on the attention check questions responded quite differently to the tax incentives in the task. I find when analyzing the interaction in the female-only subsample that the effect of eligibility determination complexity is significant given a credit structure ($F = 3.700$, $p = .056$, Bonferroni adjustment for multiple comparisons), but not in a deduction structure ($F = 2.640$, $p = .105$, Bonferroni adjustment for multiple comparisons). Stated differently, the effect of incentive structure is significant given high eligibility determination complexity ($F = 6.944$, $p = .009$, Bonferroni adjustment for multiple comparisons), but is not significant when eligibility determination complexity is low. Within the credit structure, a shift from low to high eligibility determination complexity leads to a shift in *Recommendation* score adjusted means from 8.30 to 7.53 – a significant shift away from the incentivized hybrid model. The adjusted means for males and females are plotted below in Figure 7.

Table 11

Analysis of *Recommendation* for Subsamples by Gender[1]

Panel A: *Recommendation* Descriptive Statistics by Gender

	Male			Female		
Group[2]	**Adj. Mean**[3]	**Std. Error**	**n**	**Adj. Mean**[3]	**Std. Error**	**n**
Low / Credit	7.285	.433	39	8.300	.264	64
Low / Deduction	7.919	.393	47	7.986	.244	75
High / Credit	7.853	.515	27	7.533	.299	50
High / Deduction	7.455	.423	41	8.540	.238	78

Panel B: ANCOVA Results for Males

Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**[4]	
Pollution[3]	189.083	1	189.083	26.638	<.001	***
System_Complex[3]	7.837	1	7.837	1.104	.295	
EligCondition	.100	1	.100	.014	.906	
IncStructureCondition	.504	1	.504	.071	.790	
EligCondition*IncStructureCondition	9.318	1	9.318	1.313	.254	
Error	1050.522	148	7.098			

Panel C: ANCOVA Results for Females

Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**[4]	
Pollution[3]	163.920	1	163.920	37.091	<.001	***
System_Complex[3]	15.112	1	15.112	3.419	.066	*
EligCondition	.728	1	.728	.165	.685	
IncStructureCondition	7.680	1	7.680	1.738	.189	
EligCondition*IncStructureCondition	28.059	1	28.059	6.349	.012	**
Error	1153.470	261	4.419			

Table 11 (continued)

Panel D: Post Hoc Analysis of Simple Effects for Females

Source	**df**	**Mean Square**	**F**	**Sig.**[4]	
Effect of Eligibility Determination Complexity given Credit	261	16.351	3.700	.056[5]	*
Effect of Eligibility Determination Complexity given Deduction	261	11.668	2.640	.105[5]	
Effect of Incentive Structure given Low Eligibility Complexity	261	3.371	.763	.383[5]	
Effect of Incentive Structure given High Eligibility Complexity	261	30.690	6.944	.009[5]	***

Notes:

[1]The table presents adjusted descriptives and analysis of covariance results for subsamples constructed to exclusively include male participants **not** correctly answering all three "advanced" attention check questions and female participants **not** correctly answering all three "advanced" attention check questions.

[2]Group: participants were randomly assigned to four treatment groups featuring combinations of eligibility determination complexity and tax incentive structure - "Low" / "High" = low / high eligibility determination complexity, "Credit" / "Deduction" = credit / deduction tax incentive structure

[3]Adjusted means calculated with the following covariate values: *Pollution* = 7.53, *System_Complex* = 7.05 for males; *Pollution* = 7.58, *System_Complex* = 7.04 for females.

[4]*,**,*** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. All reported p-values are two-tailed.

[5] All p-values reported for simple effects are based on pairwise comparisons of estimated marginal means, which reflect a Bonferroni adjustment for multiple comparisons.

Variable Definitions:

Recommendation: participants responded to "Considering the information presented on your friend's vehicle purchase alternatives, please indicate your recommendation using the following scale:" using an 11-point sliding scale ranging from 0 ("would definitely recommend the traditional (gas) model") to 10 ("would definitely recommend the hybrid model")

EligCondition: participants were randomly assigned to a group featuring a tax incentive with low (2 factors to consider) or high (8 factors to consider) eligibility determination complexity

IncStructureCondition: participants were randomly assigned to a group featuring a tax incentive structured as a credit or a deduction

Pollution: (a covariate) participants responded to "I believe that vehicle-related pollution is harmful to the environment and reducing this pollution is important to me" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly agree")

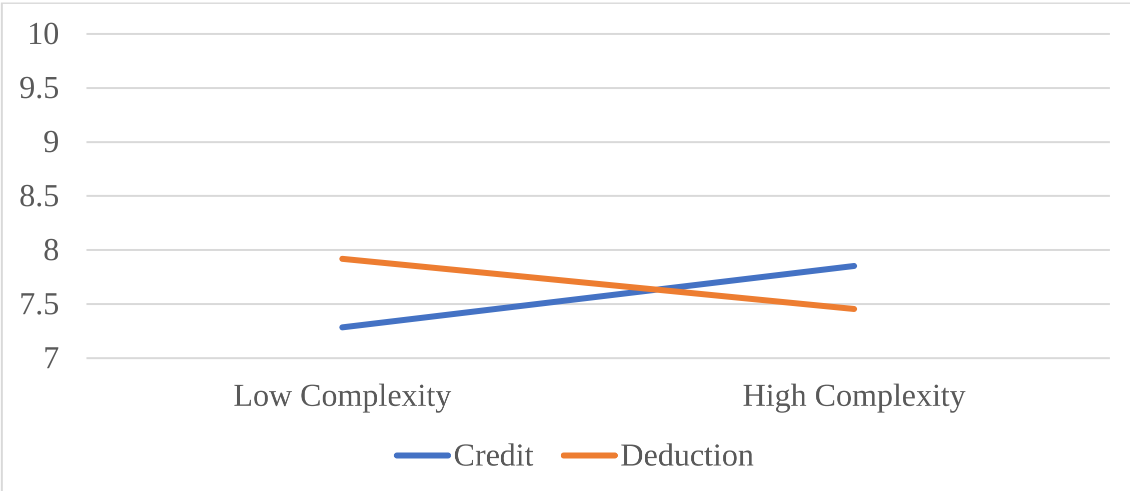
Table 11 (continued)

System_Complex: (a covariate) participants responded to "I believe that the federal tax system in the United States is too complex" using an 11-point sliding scale ranging from 0 ("strongly disagree") to 10 ("strongly disagree")

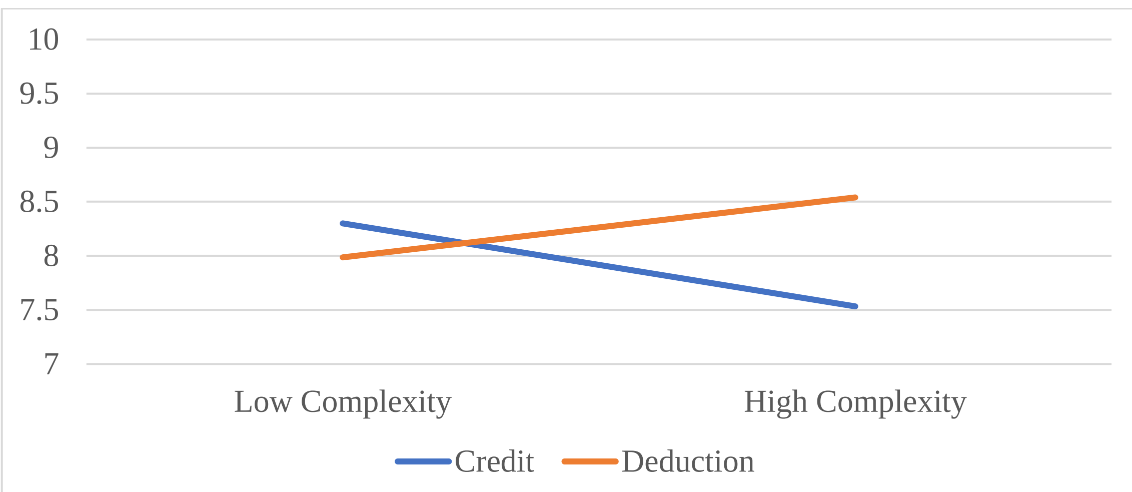
Figure 7

Effects of Eligibility Determination Complexity and Incentive Structure on *Recommendation* for Subsamples[1] by Gender

Panel A: Actual Adjusted Means for Males



Panel B: Actual Adjusted Means for Females



Note:
[1]The figure plots adjusted means for subsamples constructed to exclusively include male participants **not** correctly answering all three "advanced" attention check questions and female participants **not** correctly answering all three "advanced" attention check questions.

V. CONCLUSION

In this study, I conduct an experiment to examine whether eligibility determination complexity and tax incentive structure affect taxpayers' willingness to engage in tax-incentivized behavior. In the task, which is adapted from Morrow and Rupert (2015), I ask participants to make a recommendation to a friend deciding between two nearly-identical vehicle purchase alternatives – a traditional (gas) model and a hybrid model. Participants are informed that a federal income tax incentive is available for eligible taxpayers purchasing the hybrid model. Participants recruited through Amazon Mechanical Turk were randomly assigned to one of four treatment conditions that manipulated eligibility determination complexity (low complexity / high complexity) and tax incentive structure (credit / deduction).

My study answers a call for additional research on tax incentive complexity by Bobek et al. (2016), as I predict and find evidence that suggests eligibility determination complexity can significantly impact the behavior of taxpayers responding to tax incentives under some modeling conditions. Specifically, I find evidence that taxpayers are more likely to respond to tax incentives when determining eligibility is relatively easy. Analyzing subsamples constructed to exclusively include participants correctly answering various combinations of attention check questions, I find that participants responding to a tax incentive with low eligibility determination complexity provided significantly stronger recommendations in favor of the tax-incentivized hybrid model than those responding to a tax incentive featuring high eligibility determination complexity.

I also predict, but do not find evidence that tax incentive structure *alone* influences taxpayer response to tax incentives. Participants responding to a tax incentive structured as a tax credit provided recommendations that were not significantly different from those provided by participants responding to an incentive structured as a tax deduction. Further, I do not find this result to differ between younger and older taxpayers – incentive structure *alone* did not influence recommendations for participants of any age or level of tax return experience. This finding is mixed in its consistency with the results of Morrow et al. (2018), which provided evidence of a deduction preference *only* among younger, less experienced taxpayers. While Morrow et al. (2018) find evidence that only older, more experienced taxpayers act rationally when responding to tax incentives of different structures but identical economic values (i.e., they have no preference for one structure over the other), I find evidence of this rational behavior in participants of all ages and experience levels.

Although I do not predict an interaction, I investigate the possibility of an interaction between eligibility determination complexity and incentive structure as a research question. When analyzing certain subsamples of interest, I find that the main effect of eligibility determination complexity diminishes. I find evidence instead to suggest that taxpayers are only influenced by eligibility determination complexity when responding to tax incentives structured as credits. Specifically, taxpayers responding to credits seem to be less likely to behave as incentivized when the credit features a high level of eligibility determination complexity. The results of my study, therefore, are consistent with Morrow and Rupert (2015), which provides evidence that taxpayers are more likely to respond to tax incentives when dealing with a less complex incentive. I extend Morrow and Rupert (2015), however, by providing evidence suggesting that this effect may only apply to tax incentives structured as credits.

The effects of these variables seem to vary across different groups of taxpayers. Taxpayers most familiar and comfortable with the mechanics of our tax system (those represented in my study by participants correctly answering attention check questions at high rates) seem to be less likely to respond to tax incentives of either structure (credit or deduction) when eligibility determination complexity is high (a main effect of eligibility determination complexity). It seems, however, that taxpayers in general – those represented in my study by broader subsamples not constructed through attention check performance – are only less likely to respond to tax incentives with high eligibility determination complexity when the incentives are structured as credits.

This finding of an interaction in my study is an important extension of the tax incentive complexity literature. Evidence suggesting the effect of a form of tax incentive complexity (eligibility determination complexity in my study) depends on the structure of the tax incentive is an important finding as we interpret the results of existing studies in this area (i.e., Morrow and Rupert 2015 and Bobek et al. 2016) and continue to develop new studies aimed at understanding the effect of tax incentive complexity on taxpayer behavior. When possible and appropriate, researchers studying this effect should consider the possibility of a tax incentive structure interaction during the design phase of future experiments.

I also find some evidence of a difference in taxpayer feelings toward the incentive structures as participants responding to a tax credit indicated a significantly higher level of certainty regarding the actual tax effect of the tax incentive encountered in the task than those responding to a tax deduction. I provided participants with the actual calculations of tax, effectively holding constant calculation complexity. So, this finding suggests that taxpayers are in some way uncomfortable with the relationship between deductions and the marginal tax rate.

While prior literature has detailed taxpayer discomfort in using and interacting with marginal tax rates (i.e., Fujii and Hawley 1988, Rupert and Fischer 1995, Rupert and Wright 1998, and Rupert et al. 2003), I find evidence to suggest that the discomfort is present even when taxpayers are *not* required to incorporate the marginal tax rate into calculations.

Finally, the gender-related results of my study are mixed in their consistency with prior literature. In all of the analysis presented above on the main samples of interest, I do not find evidence to suggest gender is significantly related to *Recommendation.* This finding is consistent with Morrow et al. (2018) – gender was included in all regression models reported in their study, but was never significant. On the other hand, in my analysis of subsamples constructed to exclusively include participants **not** answering various combinations of attention check questions, I find that gender *is* significantly related to *Recommendation.* This finding is consistent with Morrow and Rupert (2015) – gender is a significant covariate in the main ANCOVA analysis provided in their study. These mixed results should lead to a close examination of the effect of gender in future studies as it seems, from the results of my study, that the effect of gender might only affect certain subsamples and, by extension, certain subsets of the population of taxpayers.

This study makes several other important contributions. First, it extends the tax literature that addresses the effect of complexity on the effectiveness of tax incentives by addressing a previously unexplored aspect of complexity – eligibility determination complexity. This aspect of complexity is important because eligibility determination is often determinable without detailed calculations and estimations of tax effects. Eligibility determination, therefore, is a decision factor a taxpayer can more easily consider before making a decision than many other factors in the decision context of a tax incentive.

My study also expands this stream of tax literature by further addressing the effect of a variable we know very little about - incentive structure. My study is one of the first to incorporate a design that does not hold constant incentive structure. As stated above, this variable can only be studied reliably using an experimental methodology as tax incentives are delivered to taxpayers as tax credits or tax deductions. I employ a design that allows me to investigate taxpayer response to exactly the same tax incentive delivered as a credit and a deduction.

My study also provides evidence that should be of interest to tax policymakers as I find that even a modest change in eligibility determination complexity can have a significant impact on a taxpayer's response to a tax incentive. This information should be important to policymakers writing new and modifying existing tax laws aimed at changing taxpayer behavior. Developing a better understanding of the effect of tax incentive structure should be important to policymakers for the same reason. As noted above, Batchelder et al. (2006), Stegmaier (2008), and others use equity and efficiency arguments to advocate in favor of a move to exclusively use the refundable tax credit structure. Given tax incentives with low levels of eligibility determination complexity, this could be a reasonable and equitable approach. The results of my study, however, suggest that taxpayers responding to tax credits featuring high levels of eligibility determination complexity may be less likely to behave as incentivized. When high eligibility complexity is required in a tax incentive aimed at changing taxpayer behavior, it seems policymakers should actually favor the deduction structure.

Finally, this study also contributes to the literature that addresses the take-up of social benefits as it extends our understanding of the effect of hassle costs across different programs and demographics. The same hassle cost (that of determining eligibility) that keeps taxpayers with the lowest levels of income from applying for social benefits like Medicaid and taking advantage of the EITC also seems to make taxpayers of diverse income levels less likely to engage in tax-incentivized behaviors. I find that this may be especially true within tax incentives structured as credits, which as noted above, are championed by many legal experts as the most appropriate structure for tax incentives. These experts, it seems, are lobbying for a wholesale shift in the direction of an incentive structure that could lead to poor taxpayer response to incentives with high levels of eligibility determination complexity.

This study has multiple limitations that lead to future research opportunities in the context of complexity in tax incentives. I made a design choice in my study to manipulate tax incentive structure as deduction for adjusted gross income vs. credit. This is a limitation in that although the two types of deductions affect tax in the same manner, I am unable to rule out the possibility that taxpayers could respond differently to tax incentives structured as deductions from adjusted gross income (itemized deductions). But, this limitation also provides opportunities for future research as the type of deduction can and should be manipulated in future studies.

The Tax Cuts and Jobs Act of 2017 (hereafter, TCJA 2017) certainly changed the landscape for tax incentives. During the 2016 tax year (pre-TCJA 2017), approximately 30 percent of individual taxpayers elected to itemize deductions – a majority of taxpayers claimed the standard deduction (IRS 2018, 20). These numbers, however, reflect taxpayer deduction behavior when the standard deduction was approximately half the amount it was for the 2018 tax year (post-TCJA 2017). The increases in standard deduction amounts will certainly lead to an even smaller percentage of the population electing to itemize deductions, and the discussion of deduction versus credit for tax incentives will be affected. Howard Gleckman, senior fellow at the Urban-Brookings Tax Policy Center, predicted that less than ten percent will itemize post-TCJA 2017 (Gleckman 2017). His estimate was reasonably accurate – early data released by the IRS reveals that approximately 10.4 percent of taxpayers filing 2018 tax returns through July 2019 chose to itemize deductions (IRS 2019b).

This change in the incentive landscape could lead to some combination of two possible outcomes. One possibility is that policymakers could begin to rely primarily on credit structures for new incentives while shifting existing incentives from itemized deduction to credit structures. Another alternative would be to shift existing and new incentives from deductions from adjusted gross income (itemized deductions) to deductions for adjusted gross income (or "above-the-line deductions") (Gleckman 2017). Although the landscape has changed drastically, it is highly unlikely that policymakers will adopt a model that exclusively uses credit structures to deliver tax incentives. If this shift does occur, I provide evidence that it could negatively impact taxpayer response when eligibility determination complexity is high. Until then, developing a better understanding of how incentive structure affects taxpayer reaction to incentives will continue to be an important issue.

Additionally, my study does not manipulate the refund/tax due position of the taxpayer. In fact, my instrument ends the tax calculation presented to participants without presenting tax prepayment or a tax due / tax refund position. I find that participants in my study were significantly influenced in the direction of the incentivized hybrid model based on the tax savings alone. Future research could extend my study by considering whether those tax savings differentially affect taxpayer behavior when leading to a reduction of tax due vs. an increase in tax refund.

Another factor not addressed or manipulated in my study is the amount of time that passes between the decision to behave in the tax-incentivized direction and the filing of a tax return that allows a taxpayer to realize the related tax benefit. Again, future research could consider the effect of this time lag on taxpayer response to tax incentives.

Finally, my study features a choice between comparable alternatives for which the after-tax, long-term cost of the tax-incentivized alternative is approximately equal to the cost of the alternative not incentivized. Many participants in my study indicated this to be an important factor in the recommendation in favor of the hybrid model. Future research should also consider taxpayer behavior in choice environments where the tax-incentivized alternative has a greater after-tax cost than the non-incentivized alternative.

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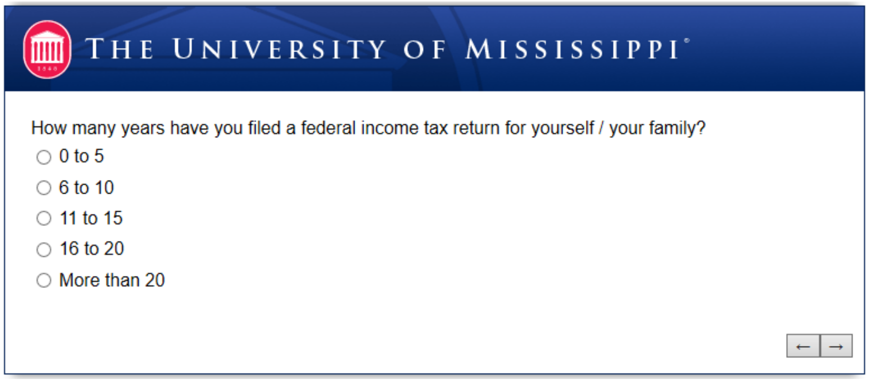
APPENDIX

Appendix: Full Experimental Instrument

[Screening question, preceded only by consent page]



THE UNIVERSITY OF MISSISSIPPI

How many years have you filed a federal income tax return for yourself / your family?

- 0 to 5
- 6 to 10
- 11 to 15
- 16 to 20
- More than 20

[Introduction]

THE UNIVERSITY OF MISSISSIPPI

Recently, your friend decided to purchase a new car and requested your opinion before making a final decision. After several weeks of extensive research, your friend narrowed down the choices to two versions of the same model. The two models are essentially the same but with one significant difference – one model is a traditional car, which runs on gas, while the other model is a hybrid car, which runs on a combination of gas and electricity.

Your friend is having a tough time deciding between the two. Your friend is comfortable with the style, handling, and acceleration of each model. In addition, reliability and safety of both cars are relatively similar, and your friend's insurance company has quoted comparable premiums for both models. Your friend has saved enough cash to purchase either car without financing. Each vehicle includes an identical five-year limited warranty, which also covers routine maintenance and tune-ups. At the end of five years, your friend expects to sell the car that was purchased and expects both cars to sell for equivalent prices.

Basic information is provided for each model below, but a detailed set of specifications will be provided later.

	Traditional (Gas) Model	**Hybrid Model**
Purchase Price	$24,000	$27,500
Estimated Sales Tax	$1,440	$1,650
Estimated Miles per Gallon (MPG)	28	40
Estimated 5-year cost to fuel vehicle	$5,000*	$3,500*

*Estimated cost of gasoline over five-year period to travel 12,000 miles per year (60,000 total miles)

→

[Eligibility Complexity = Low]

THE UNIVERSITY OF MISSISSIPPI®

Per the dealer, your friend **could be** eligible for a federal tax incentive that would reduce federal income tax **if your friend purchases the hybrid model**. Because each taxpayer has different financial circumstances, the dealer has chosen not to give guidance regarding eligibility for the tax incentive. Your friend was able to determine that the following requirements must be met for a hybrid vehicle **purchase** to be eligible for the tax incentive:

- vehicle must have a gross weight of less than 5,000 pounds
- vehicle must have driving range of at least 400 miles when fully-fueled

A detailed list of specifications for each vehicle is provided below:

	Traditional (Gas)	**Hybrid**
Purchase Price	$24,000	$27,500
Estimated Sales Tax	$1,440	$1,650
Estimated 5-year Fuel Cost	$5,000	$3,500
Vehicle Length	191.8 inches	191.8 inches
Vehicle Height	58.2 inches	58.0 inches
Vehicle Width, including mirrors	83.5 inches	83.5 inches
Gross Vehicle Weight	3,472 pounds	3,668 pounds
Seating Capacity	5	5
Passenger Volume	102.8 cubic feet	102.8 cubic feet
Trunk Volume	16 cubic feet	12 cubic feet
Estimated MPG, city	25	43
Estimated MPG, highway	31	38
Fuel Tank Capacity	14 gallons	14 gallons
Estimated Full-Tank Range	392 miles	560 miles
Engine Type	2.5L 4-cylinder	2.0L hybrid engine
Engine Power	175 horsepower @ 6,000 rpm	141 horsepower @ 6,000 rpm
Engine Torque	175 lb.-ft. @ 4,500 rpm	129 lb.-ft. @ 4,000 rpm
Maximum Speed	121 mph	109 mph
Maximum Speed – Electric Mode	N/A	85 mph
Battery Type	N/A	1.4 kwh lithium-ion
Battery Peak Power	N/A	35 kw
Transmission Type	Six-speed, automatic	Electronic continuous / variable

← →

[Eligibility Complexity = High]

THE UNIVERSITY OF MISSISSIPPI

Per the dealer, your friend **could be** eligible for a federal tax incentive that would reduce federal income tax **if your friend purchases the hybrid model**. Because each taxpayer has different financial circumstances, the dealer has chosen not to give guidance regarding eligibility for the tax incentive. Your friend was able to determine that the following requirements must be met for a hybrid vehicle **purchase** to be eligible for the tax incentive:

- vehicle must have a gross weight of less than 5,000 pounds
- vehicle must have driving range of at least 400 miles when fully-fueled
- the difference between the vehicle's fuel efficiency (mpg) for city driving and the vehicle's fuel efficiency (mpg) for highway driving must be less than 10 mpg
- vehicle's fuel tank must have a capacity of at least 12 gallons
- vehicle must have an electric mode top speed in excess of 70 miles per hour (mph)
- vehicle must have seating capacity of at least 4
- vehicle must have a passenger volume of at least 75 cubic feet
- vehicle's battery must have a peak power rating of at least 30 kw

A detailed list of specifications for each vehicle is provided below:

	Traditional (Gas)	**Hybrid**
Purchase Price	$24,000	$27,500
Estimated Sales Tax	$1,440	$1,650
Estimated 5-year Fuel Cost	$5,000	$3,500
Vehicle Length	191.8 inches	191.8 inches
Vehicle Height	58.2 inches	58.0 inches
Vehicle Width, including mirrors	83.5 inches	83.5 inches
Gross Vehicle Weight	3,472 pounds	3,668 pounds
Seating Capacity	5	5
Passenger Volume	102.8 cubic feet	102.8 cubic feet
Trunk Volume	16 cubic feet	12 cubic feet
Estimated MPG, city	25	43
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Fuel Tank Capacity	14 gallons	14 gallons
Estimated Full-Tank Range	392 miles	560 miles
Engine Type	2.5L 4-cylinder	2.0L hybrid engine
Engine Power	175 horsepower @ 6,000 rpm	141 horsepower @ 6,000 rpm
Engine Torque	175 lb.-ft. @ 4,500 rpm	129 lb.-ft. @ 4,000 rpm
Maximum Speed	121 mph	109 mph
Maximum Speed – Electric Mode	N/A	85 mph
Battery Type	N/A	1.4 kwh lithium-ion
Battery Peak Power	N/A	35 kw
Transmission Type	Six-speed, automatic	Electronic continuous / variable

← →

[Tax Incentive Structure = Credit]

THE UNIVERSITY OF MISSISSIPPI

The federal government provides the incentive in the form of a **tax credit**, which reduces the amount of tax owed by a taxpayer on a dollar-for-dollar basis (one dollar of credit reduces tax due by one dollar). The credit for this vehicle is limited to $2,200. Your friend is a single taxpayer with no children, whose only source of income is a $62,500 salary received as an employee. Also, your friend lives and works in a state that does not impose a state income tax.

Your friend will not file a federal tax return for the current tax year until approximately two months after the end of the tax year, but was able to provide you with some estimates. Your friend will deduct the standard deduction for the current tax year. Your friend's approximate tax situation for the current year given no vehicle purchase, the purchase of the traditional (gas) model, and the purchase of the hybrid model (assuming eligibility for the tax credit) would be as follows:

	No vehicle purchased	**Traditional (gas) model purchased**	**Hybrid model purchased**
Gross Income	$62,500	$62,500	$62,500
Less: Deductions for adjusted gross income (above-the-line deductions)	-	-	-
Adjusted Gross Income	$62,500	$62,500	$62,500
Less: Deductions from adjusted gross income (standard deduction)	($12,000)	($12,000)	($12,000)
Taxable Income	$50,500	$50,500	$50,500
Tax Rates Applied			
Tax Before Considering Credits	$6,969	$6,969	$6,969
Less: Tax Credits	-	-	($2,200)
Tax Due	$6,969	$6,969	$4,769

[Tax Incentive Structure = Deduction]

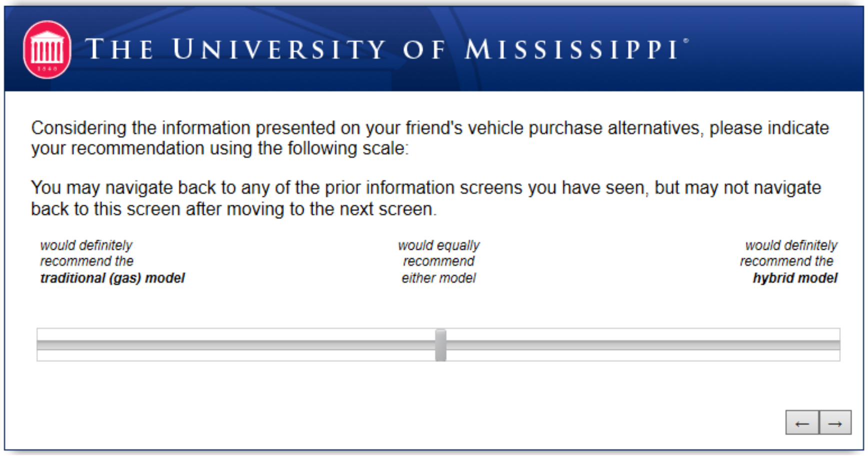
THE UNIVERSITY OF MISSISSIPPI

The federal government provides the incentive in the form of a **tax deduction** (specifically, a deduction for adjusted gross income or an "above-the-line" deduction), which reduces the amount of your income subject to tax at year-end. The deduction for this vehicle is limited to $10,000. Your friend is a single taxpayer with no children, whose only source of income is a $62,500 salary received as an employee. Also, your friend lives and works in a state that does not impose a state income tax.

Your friend will not file a federal tax return for the current tax year until approximately two months after the end of the tax year, but was able to provide you with some estimates. Your friend will deduct the standard deduction for the current tax year. Your friend's approximate tax situation for the current year given no vehicle purchase, the purchase of the traditional (gas) model, and the purchase of the hybrid model (assuming eligibility for the tax deduction) would be as follows:

	No vehicle purchased	**Traditional (gas) model purchased**	**Hybrid model purchased**
Gross Income	$62,500	$62,500	$62,500
Less: Deductions for adjusted gross income (above-the-line deductions)	-	-	($10,000)
Adjusted Gross Income	$62,500	$62,500	$52,500
Less: Deductions from adjusted gross income (standard deduction)	($12,000)	($12,000)	($12,000)
Taxable Income	$50,500	$50,500	$40,500
Tax Rates Applied			
Tax Before Considering Credits	$6,969	$6,969	$4,769
Less: Tax Credits	-	-	-
Tax Due	$6,969	$6,969	$4,769

[Dependent variable = Recommendation]



[Motivation and additional information]

THE UNIVERSITY OF MISSISSIPPI

Please use the space below to explain what factors motivated the vehicle purchase recommendation you made to your friend.

Would you have been more comfortable making your recommendation if you had additional information?

- Yes
- No
- Not sure

If you answered yes, what additional information would you have found to be useful / important?

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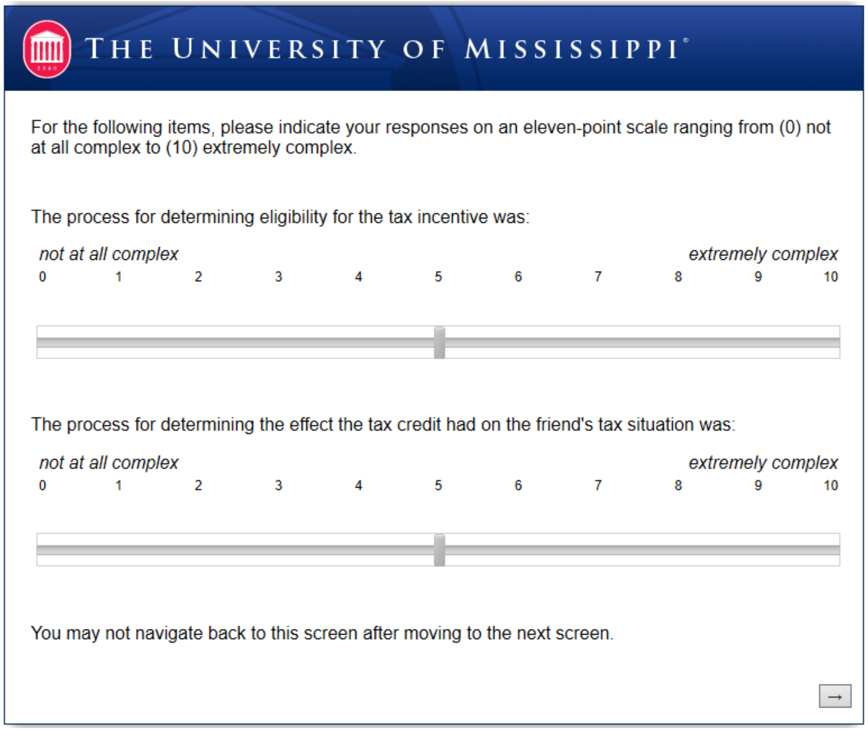
[Manipulation checks for participants assigned to a credit condition]



THE UNIVERSITY OF MISSISSIPPI®

For the following items, please indicate your responses on an eleven-point scale ranging from (0) not at all complex to (10) extremely complex.

The process for determining eligibility for the tax incentive was:

not at all complex ... *extremely complex*

0 1 2 3 4 5 6 7 8 9 10

The process for determining the effect the tax credit had on the friend's tax situation was:

not at all complex ... *extremely complex*

0 1 2 3 4 5 6 7 8 9 10

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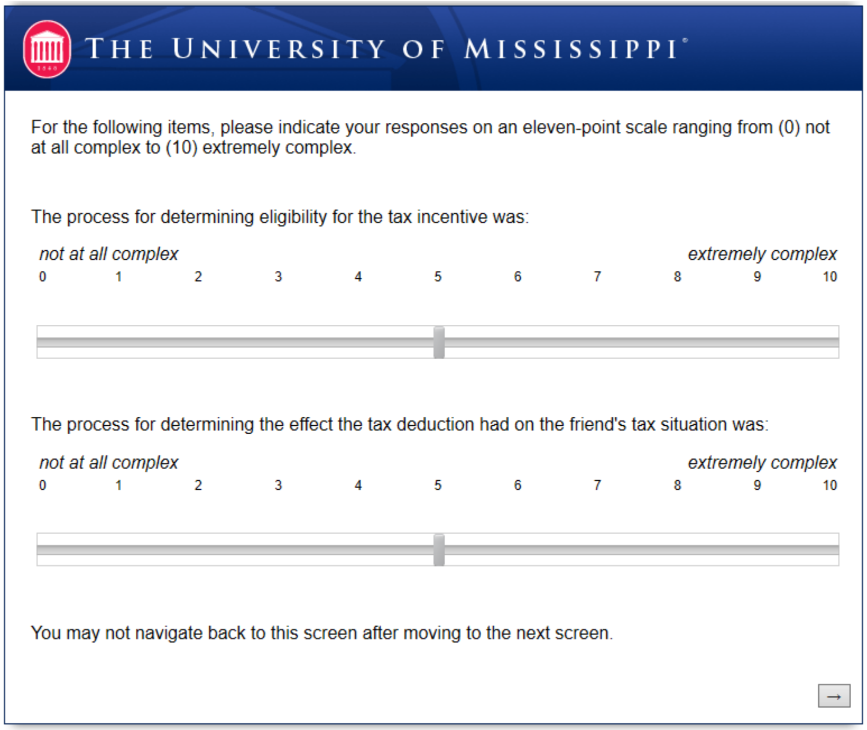
[Manipulation checks for participants assigned to a deduction condition]



THE UNIVERSITY OF MISSISSIPPI

For the following items, please indicate your responses on an eleven-point scale ranging from (0) not at all complex to (10) extremely complex.

The process for determining eligibility for the tax incentive was:

not at all complex ... *extremely complex*

0 1 2 3 4 5 6 7 8 9 10

The process for determining the effect the tax deduction had on the friend's tax situation was:

not at all complex ... *extremely complex*

0 1 2 3 4 5 6 7 8 9 10

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[Attention check questions]

THE UNIVERSITY OF MISSISSIPPI

Please answer the following questions related to the task you just completed:

For which vehicle was the purchase price highest?

- ○ Traditional (Gas) Model
- ○ Hybrid Model
- ○ Do not know

For which vehicle was the five-year total cost of fuel highest?

- ○ Traditional (Gas) Model
- ○ Hybrid Model
- ○ Do not know

What was the friend's eligibility status regarding the tax incentive for the hybrid vehicle?

- ○ The friend was definitely eligible for the incentive
- ○ The friend was definitely not eligible for the incentive
- ○ Do not know
- ○ Did not consider eligibility

The tax incentive that was explained for the purchase of an eligible hybrid vehicle was structured as which of the following?

- ○ Deduction
- ○ Credit
- ○ Income Exclusion
- ○ None of these
- ○ Do not know

How much actual tax savings would your friend receive if your friend purchased the hybrid model and utilized the tax incentive explained earlier?

- ○ $0
- ○ $500
- ○ $2,200
- ○ $5,000
- ○ $10,000

How will you be paid for your participation in this study?

- ○ A flat fee of $2.00
- ○ A flat fee of $1.00, plus $0.10 for each minute spent answering the questions
- ○ A flat fee of $1.00
- ○ A fee of $1.00, plus $0.10 for each word provided on open-answer questions

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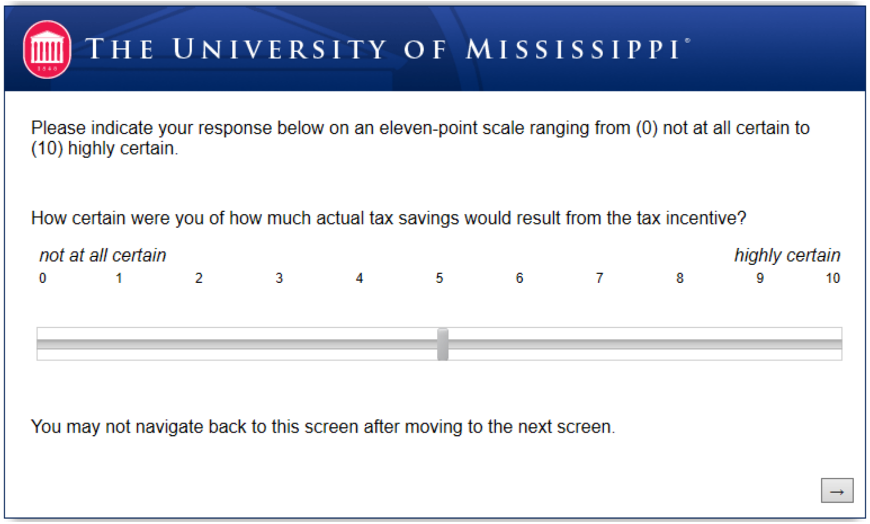
[Certainty]


THE UNIVERSITY OF MISSISSIPPI
Please indicate your response below on an eleven-point scale ranging from (0) not at all certain to (10) highly certain.
How certain were you of how much actual tax savings would result from the tax incentive?
not at all certain
highly certain
0 1 2 3 4 5 6 7 8 9 10
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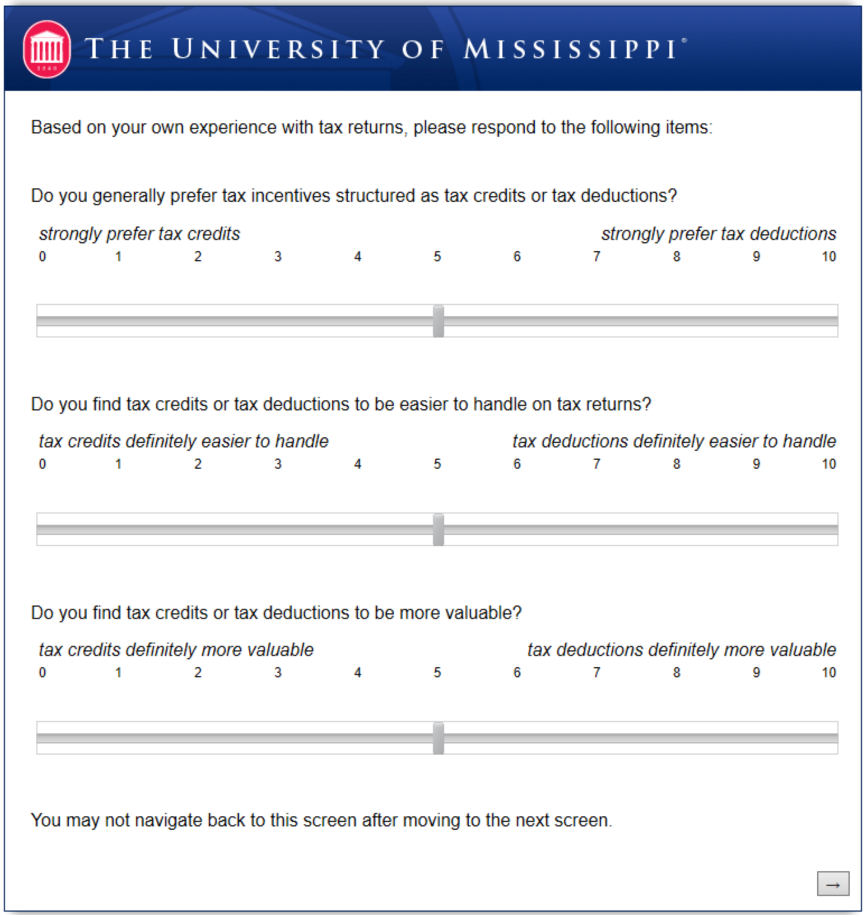
[Credits vs. deductions]


THE UNIVERSITY OF MISSISSIPPI

Based on your own experience with tax returns, please respond to the following items:

Do you generally prefer tax incentives structured as tax credits or tax deductions?

strongly prefer tax credits … *strongly prefer tax deductions*

0 1 2 3 4 5 6 7 8 9 10

Do you find tax credits or tax deductions to be easier to handle on tax returns?

tax credits definitely easier to handle … *tax deductions definitely easier to handle*

0 1 2 3 4 5 6 7 8 9 10

Do you find tax credits or tax deductions to be more valuable?

tax credits definitely more valuable … *tax deductions definitely more valuable*

0 1 2 3 4 5 6 7 8 9 10

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[Controls]

THE UNIVERSITY OF MISSISSIPPI

Please indicate the extent to which you agree with the following statements using an eleven-point scale ranging from (0) strongly disagree to (10) strongly agree.

I believe that vehicle-related pollution is harmful to the environment and reducing this pollution is important to me.

strongly disagree *strongly agree*

0 1 2 3 4 5 6 7 8 9 10

I believe that the federal tax system in the United States is too complex.

strongly disagree *strongly agree*

0 1 2 3 4 5 6 7 8 9 10

I am aware of the actual federal tax incentive that exists for hybrid vehicle purchases and this knowledge influenced my recommendation.

strongly disagree *strongly agree*

0 1 2 3 4 5 6 7 8 9 10

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[Demographic information]

THE UNIVERSITY OF MISSISSIPPI

What is your gender?

○ Male

○ Female

○ Prefer not to answer

What is your age in years?

Have you ever filed a federal income tax return on which you reported a deduction for adjusted gross income (or an above-the-line deduction)?

○ Yes

○ No

○ Do not know

Have you ever filed a federal income tax return on which you itemized deductions (instead of deducting the standard deduction)?

○ Yes

○ No

○ Do not know

Have you ever filed a federal income tax return on which you reported a tax credit?

○ Yes

○ No

○ Do not know

Have you ever purchased a hybrid or electric vehicle?

○ Yes

○ No

Are you currently planning to purchase a new personal vehicle within the next year?

○ Yes

○ No

What is your annual household income?

○ $0 - $24,999

○ $25,000 - $49,999

○ $50,000 - $74,999

○ $75,000 - $99,999

○ > $100,000

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VITA

Joshua L. Simer

Education and Certification

Tennessee Technological University, Cookeville, TN

- Master of Business Administration – Accounting Focus • 2011
- Bachelor of Science in Business Administration – Accounting • 2009

Certification: Certified Public Accountant (Inactive), State of Tennessee

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Research

Interest: Taxation, tax policy, behavior of taxpayers and tax professionals
Methodology: Behavioral

Published Research:
"Barber Conable: A Tribute to His Contributions to Tax Law and Lessons for Tax Education" (with Tonya K. Flesher, University of Mississippi, Professor Emerita). *Accounting Historians Journal*, June 2019

"Charities: Use Care in Discussing Tax Deductions". *Arkansas Business*, October 2019

Dissertation:
"The Effects of Eligibility Complexity and Incentive Structure on the Relationship between Tax Incentives and Taxpayer Behavior"

Committee: Dr. Morris Stocks (chair), Dr. Christine Cheng, Dr. Jeremy Griffin, and Dr. John Bentley (external) of the University of Mississippi

Working Papers:
"Self-Employed Health Insurance Deduction: Nice Tax Break or Gross Inequity?" (with Andrew Almand, Henderson State University). Under first round review at *The CPA Journal.*

"The Effect of Client Profitability on Tax Preparer Effort" (second year paper, advised by Dr. Kendall Bowlin and Dr. Jeff Pickerd). Revising for journal submission.

Presentations:
"The Effects of Eligibility Complexity and Incentive Structure on the Relationship between Tax Incentives and Taxpayer Behavior"

- Behavioral Tax Symposium, Washington, D.C.; June 2019
- University of Mississippi, Oxford, MS (dissertation proposal); May 2019

"Barber Conable: A Tribute to His Contributions to Tax Law and Lessons for Tax Education"

- Coastal Carolina University, Conway, SC; November 2018
- University of Central Arkansas, Conway, AR; September 2018
- AAA Annual Meeting, San Diego, CA; August 2017

"Self-Employed Health Insurance Deduction: Nice Tax Break or Gross Inequity?"

- Coastal Carolina University, Conway, SC; November 2018
- University of Central Arkansas, Conway, AR; September 2018

"The Effect of Client Profitability on Tax Preparer Effort"

- Coastal Carolina University, Conway, SC; November 2018
- University of Central Arkansas, Conway, AR; September 2018
- University of Mississippi, Oxford, MS (second year paper presentation); February 2018

Conference Participation

Behavioral Tax Symposium, Washington, D.C., 2019
AAA Annual Meeting, San Diego, CA, 2017
Behavioral Tax Symposium, Washington, D.C., 2017
ATA Mid-Year Meeting, Phoenix, AZ, 2017

Teaching

Interests: Individual taxation, tax policy, financial accounting, managerial / cost accounting
Experience:
University of Central Arkansas – Instructor

- Individual Taxation (F-2019, S-2020)
- Principles of Accounting II (S-2020)

University of Mississippi – Graduate Instructor

- Introduction to Accounting Principles I (Sum-2018, Sum-2017)
- Introduction to Accounting Principles II (S-2019, S-2017, F-2016, Sum-2016, S-2016)
- Income Taxes I (F-2018, S-2018, F-2017)

Professional Experience

Community Health Systems, Franklin, TN July 2014-June 2015

- Corporate Tax Accountant

Faulkner, Mackie & Cochran, P.C., Nashville, TN July 2011-July 2014

- Advanced Staff Accountant (Tax)

Professional Organizations

Arkansas Society of Certified Public Accountants, 2019 – Present
American Accounting Association, 2015 - Present
American Institute of Certified Public Accountants, 2012 - Present
Tennessee Society of Certified Public Accountants, 2012 - Present

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Awards/Honors

Graduate Instructor Excellence in Teaching Award, CETL, University of Mississippi - 2019
Patterson School of Accountancy Doctoral Teaching Award - 2018
University of Mississippi Graduate Achievement Award - 2017
ESPN The Magazine Academic All-America – Men's at Large Team (Golf) - 2010
Tennessee Technological University NCAA Man of the Year - 2010
Ohio Valley Conference Academic Medal(s) of Honor – 2007, 2008, 2009, 2010
Beta Gamma Sigma – Tennessee Technological University