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Demand for Services: Determinants of Tax Preparation Fees

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ABSTRACT

We empirically investigate the demand for income tax preparation services by examining factors that affect both the choice and level of utilization of service. We identify the demand factors as the taxpayer's (1) opportunity costs, (2) estimated tax savings when using a preparer, and (3) historical uncertainty in tax liability. Our panel data set allows us to measure individual-specific uncertainty, a new measure in assessing determinants of tax service demand. Consistent with prior research, choice is measured by whether a taxpayer uses a professional paid preparer. The preparer's fee is the measure of utilization level. Fee information is heavily censored in part because fees only need to be disclosed when taxpayers itemize deductions and have miscellaneous itemized deductions above the 2 percent limit. We develop a partially censored regression model to accommodate the censoring.

Similar to Cragg (1971), we decouple the choice and level of utilization models; findings indicate differences between these models. Generally, taxpayers choose paid preparers for time savings and uncertainty protection. Fees, however, reflect the purchase of time and tax savings, not uncertainty protection. These results suggest that pricing structures for professional tax preparation services could be adjusted to more closely reflect the services provided.

INTRODUCTION

Fee structures for professional service providers are rapidly evolving, as is the nature of the services demanded. Providers of income tax preparation and consulting services are no exception to this change, and it is therefore possible that the tax preparer's billing structure invoices for a set of factor inputs, largely time spent, that does not impound all costs of the consumer's service, such as saving taxpayer time, saving taxes, and providing an insurance function. Thus, understanding tax preparer product demand components is important for designing a fee structure that is competitive for the preparer on a long-term basis as well as being viewed as fair by clients.

Tax services represent approximately 38 percent of accounting industry fees (Yancey 1996), the balance being made up of audit and management advisory services. Research focusing on tax

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preparation services has developed a body of literature identifying demand choice factors (see Christian et al. 1993), but has done little to connect this demand with the market-determined fee. In this paper, we relate these factors to fees. Little has been done to understand market-determined fees because of the nature of tax return data; specifically, fee information from taxpayers is heavily censored. This is because disclosed tax preparation fees are typically lagged one year and need to be disclosed only when taxpayers are allowed an itemized deduction for them; i.e., when the taxpayer itemizes deductions and has miscellaneous deductions in excess of 2 percent of adjusted gross income. Further, we find that fees are often reported even though they are not deductible. Only 12 percent of our sample of 5,933 taxpayers reported fees; 60 percent of these reported fees are not deductible. As a result, we develop a bivariate partially censored regression model that allows for both the tax return rule-based censoring as well as random censoring.

Because of the complex nature of our data, we use a hierarchical model, analogous to one proposed by Cragg (1971). We examine both the choice and level of utilization of tax preparation services using the same data set. It seems plausible that the demand factors that influence a taxpayer's choice of whether to use a tax preparer also influence the taxpayer's decision regarding the level of service required. Anecdotal evidence in the form of newly legislated taxpayer and preparer penalties as well as the proliferation of lawsuits against tax preparers suggests that more is being purchased than tax savings (Yancey 1996). As described in the next section, we identify these demand factors as the taxpayer's (1) opportunity costs, (2) estimated tax savings when using a preparer, and (3) historical uncertainty in tax liability.

To estimate the demand models, we use data from the Ernst & Young/University of Michigan Tax Panel. This panel data set of taxpayers contains information on preparer choice for six years, although preparation fees are available for only the last three of those years.[1] We use the first five years of the panel to estimate an individual's tax savings from using a paid preparer and historical uncertainty in tax liability. The panel allows us to simplify and extend the tax savings measure of Long and Caudill (1987) to the panel data context whereas the uncertainty measure is new. The tax liability model and variable measurement section describes the panel data model that allows us to construct these measures.

Our analysis concludes with discussions of the choice and level of service models. The explanatory variables of these models are a taxpayer's opportunity costs, tax savings and historical uncertainty in tax liability. Although we develop the same basic determinants to explain both models, we do not constrain them by requiring that variable coefficients have the same sign, similar to Fin and Schmidt (1984). Indeed, findings indicate differences between the two models. Generally, taxpayers choose paid preparers for time savings and protection from uncertainty. Fees, however, reflect the purchase of time and tax savings, not uncertainty. These results suggest that pricing structures for professional tax preparation services could be adjusted to more closely reflect the services provided.

LITERATURE REVIEW: THE IDENTIFICATION OF DEMAND FACTORS

In the tax area, numerous studies have identified factors associated with preparer usage. Further, empirical and analytical studies have developed microeconomic models of taxpayer compliance considering the role of preparers; see Andreoni et al. (1998) for a recent review. Few analyses have considered the cost of the services, i.e., preparer fees.

Choice-Based Factors

Factors associated with preparer choice can be broadly classified into those associated with (1) tax savings, (2) time savings, and (3) uncertainty. With regard to tax savings, Klepper et al.

[1] Preparation fees are available for tax years 1987–89. Because fees are deductible when paid, they are lagged one year. (For example, fees for preparing the 1988 tax return are assumed to be deducted on the 1989 tax return because they are typically paid in 1989.)

(1991) model paid preparers developing strategies to reduce tax liability. This is consistent with empirical evidence showing paid preparers as exploiters of ambiguous areas of tax law (Klepper and Nagin 1989). Long and Caudill (1987) find that, for the same type of return, paid preparer returns have a lower tax liability than self-prepared returns and suggest that paid preparers save tax dollars as well as time. However, lacking data on professional fees, they acknowledge that these conclusions are tentative.

Viewing tax preparers as saving taxpayer time, Reinganum and Wilde (1991) develop a game theoretic model of taxpayer, tax preparer, and IRS behavior. They argue that even if the taxpayer knows the law and is capable of preparing an optimal return, the taxpayer may still prefer to use a preparer to reduce costs of return preparation. Identifying four equilibria that depend on whether taxpayers prefer to use tax preparers and whether the IRS prefers the same, they conclude that taxpayers prefer to use paid preparers when the penalties for noncompliance are low and efficiency gains are high.

In an IRS-commissioned study of taxpayer attitudes by Yankelovich, Skelly, and White, Inc. (1984), taxpayers were asked the primary reason for selecting a paid preparer. Their primary reasons were as follows: (1) "I am in the habit of using a paid preparer"; (2) "I wanted to save taxes"; (3) "I was afraid of making a mistake"; (4) "I wanted to save time"; and (5) "The forms were too complicated." Those taxpayers who self-prepared their returns had similar reasons for self-preparing as did those who chose a paid preparer: (1) "I always do it myself"; (2) "I want to avoid the expense of a paid preparer"; (3) "I can do it just as well as a paid preparer"; (4) "I can do it easier without a paid preparer"; and (5) "The forms have been simplified."

Archival studies identifying factors associated with the choice of a paid preparer can also be classified as supporting the time and/or tax savings roles of paid preparers. Typical results of these studies include identification of characteristics associated with preparer usage and varied efforts to connect them with a comprehensive model of preparer demand. For example, Long and Caudill (1993, 1987) use a national sample of individual income tax returns from the Internal Revenue Service's 1983 Tax Model File. In their primary result, they find complexity and marginal tax rates increasing preparer usage. In addition, they identify income, age, and self-employment status as positively associated with preparer usage. Dubin et al. (1992), using data from the Special Academic Research File of the 1979 Individual Return Taxpayer Compliance Measurement Program (TCMP), find that audit anxiety, complexity, increased age, number of exemptions, itemized deductions, low tax knowledge, self-employment, and the source of income positively impact the use of a preparer. Slemrod (1989) constructs a utility maximization model of taxpayer behavior that includes both the taxpayer's time and preparer's fees as endogenous (choice) variables for minimizing tax liability. In a two-stage procedure (the first stage controlling for selectivity bias in choice of itemization status and paid preparer usage), Slemrod (1989) identifies the presence of self-employment income and capital gains as being associated with greater expenditures of time and money on tax preparation. In addition, taxpayers with higher opportunity cost of time (and in some cases a higher marginal tax rate) are more likely to use professional assistance. Because survey data can suffer from response bias, and cross-sectional archival data can suffer from omitted variables bias, Christian et al. (1993) use panel data to mitigate these problems. In the first study to empirically separate complexity and time savings from other factors, they conclude that complexity, income level, self-employment, and time cost are positively associated with the use of a preparer. In contrast to prior studies, they find no income or marginal rate effect. Results for demographic variables depend on itemization status.

Considering uncertainty and risk, Scotchmer (1989) models the role of preparers to reduce uncertainty in reported income. She suggests that if taxpayers are risk-neutral and uncertain of their reported income, then they will tend to overreport their tax liability because the costs of overreporting are less than those of underreporting. By eliminating uncertainty, taxpayers are comfortable with reporting lower incomes. Survey data, collected by Collins et al. (1990), identifying taxpayer motivations for using paid preparers, can be closely aligned with an economic model of demand for preparer services that includes risk. Segregating their sample by taxpayer self-reported objectives of (1) tax minimization and (2) desire to file a correct return, they analyze the factors associated with preparer use. They find that choosing a preparer to minimize taxes is associated with higher income and age but lower social responsibility and tax knowledge. Filing a correct return is associated with higher value orthodoxy and return complexity, but lower tax knowledge. Their measures of risk and anxiety are not significant in either case. In addition, the reported amount of taxpayer time spent does not differ between preparation modes.

Tax Preparer Fee Studies

Research is scant on the determinants of preparer fees. In a 1982 survey and its 1989 follow-up, Slemrod and Sorum (1984) and Blumenthal and Slemrod (1992) gather data on income, education, employment, and marital status of their respondents and relate it to time and money spent on tax compliance. Although their purpose is to estimate aggregate compliance cost and identify compliance effects of the Tax Reform Act of 1986, secondary findings indicate income, self-employment, and single marital status positively relate to fees. To date, only Lin (1993) uses fees as reported on tax returns. Lin (1993) extends Long and Caudill (1987) by incorporating the preparer's fee as a reduction of tax savings in paid preparer returns and finds that paid preparers tend to provide a net savings to only higher income taxpayers. Lin (1993) addresses the censoring issue by imputing fees that were not available (approximately 95 percent of the sample). Because this technique is unreliable (Little and Rubin 1987), we use an alternative approach to address the censoring issues.

THEORETICAL MODEL AND DATA

Synthesizing the results of survey and archival research on the determinants of preparer usage, we model the demand for tax services as:

$$\text{utility of service} = f(\text{tax savings, time savings, uncertainty}).$$

The role of tax savings as an important determinant of preparer usage has been demonstrated by Long and Caudill (1987) and others described in the previous section. Slemrod (1989), Christian et al. (1993) and others have demonstrated the role of time savings. This paper introduces to empirical archival analysis the role that uncertainty plays in determining preparer usage.

It is known that the demand for insurance contracts, where protection against unforeseen loss is the only utility of the contract, is driven by uncertainty in outcomes. For example, Mossin (1969) shows that consumers will demand full protection against uninsurable events under minimal conditions. Because of their professional expertise, paid preparers reduce uncertainty in two ways, therefore providing a type of insurance contract. First, their expert knowledge should produce a tax liability that is less susceptible to change by the IRS. Second, preparers can be held legally responsible for a taxpayer's IRS penalty and interest charges related to their performance, thus reducing a taxpayer's potential liability. This paper explores the role of uncertainty in determining preparer usage. As later described, we use a taxpayer's residual standard deviation of tax liability as a measure of uncertainty.

We study utility of service in two ways. First, we examine a choice-based logistic regression model and use preparation mode to gauge the utility of service. This standard econometric model is described in, for example, Greene (1993, chapter 21). Second, we use the preparer's fee as a measure of utility of service. The assumption here is that, in a competitive market, the preparer's fee is the minimum price for a given bundle of tax savings, time savings, and uncertainty. By comparing the results of these two models, we relate the services taxpayers demand from tax preparers to the tax preparation fees.

The fee demand model is estimated using a bivariate partially censored regression model. As more fully described later, censoring is an important feature of our data. To illustrate, only about 12 percent (691 of 5,675) of our taxpayers disclosed fees paid to professional tax preparers.

Our censoring model can be thought of as a special type of bivariate extension of the Tobit model described, for example, in Maddala (1991). In the traditional univariate Tobit (censored) model, we observe the response y if it exceeds a threshold, say c, and otherwise observe c. Generally this threshold is zero. The model is then estimated using maximum likelihood. Intuitively, one can think of parameter estimates as ordinary least squares estimates with a correction for selection bias.

However, as noted by Maddala (1991), the Tobit model should not be used simply because a data set has several limit (zero) observations. For many data sets, an observed response at the threshold level indicates "*nonobservability*" (Maddala's emphasis), not truncation at the threshold level. To illustrate, suppose that the response is hours worked by an individual. The customary interpretation of a response that equals zero hours is that a choice was made not to work or, in Maddala's (1991) terminology, we did not observe the individual working. Alternatively, within the traditional Tobit framework, we would posit an underlying continuous variable that represents hours worked; the truncation of negative values of this underlying continuous variable yields zero hours worked. Although this may be appropriate for some data sets, for other data sets the limit observations represent a choice made not to work. Cragg's (1971) model allows one to decouple the choice made from the extent of work. This is done by modeling the decision to work sequentially; first the choice to work and second the extent of work. These two components are not handled simultaneously as in the Tobit model.

Our censoring model (fee demand model) is a bivariate extension of Cragg's (1971) model. We find that, in addition to fee, it is necessary to consider other miscellaneous deductions. The fee and other miscellaneous deduction variables form our bivariate response and both are subject to censoring. Although complex, the spirit of our censoring model is similar in flavor to the well-known Tobit model; the goal is to introduce "corrections" to accommodate the potential bias for nonobservability of certain types of behavior.

Data and Sample Selection

Data for this study are from the Statistics of Income (SOI) Panel of Individual Returns, a part of the Ernst & Young/University of Michigan Tax Research Database. The SOI Panel represents a simple random sample of unaudited individual income tax returns processed during tax years 1979–1990. The data are compiled from a stratified probability sample of unaudited individual income tax returns, Forms 1040, 1040A and 1040EZ, filed by U.S. taxpayers. The estimates that are obtained from these data are intended to represent all returns filed for the income tax years under review.[2] All returns processed are subjected to sampling except tentative and amended returns.

We construct a balanced panel from 1982–1984 and 1986–1989 taxpayers included in the SOI panel; this results in a full sample of 5,933 taxpayers. These years are chosen because they contain the necessary data on paid preparer usage for the estimation procedures. Specifically, these data include line-item tax return data plus an indicator variable noting the presence of a paid tax preparer for years 1982–1984 and 1986–1988. For these six years, preparation fee is available in only 1987 and 1988 for all taxpayers who employed a paid preparer, itemized their deductions, and had miscellaneous deductions in excess of 2 percent of adjusted gross income.[3]

Much of the model identification in this study is done with a randomly selected subsample (training sample) that consists of 4 percent of our sample, or 258 taxpayers. The primary function of the training sample is to facilitate identification of relations among the model variables. By splitting off a portion of the data for model identification, we do not bias our results through repeated iterations of data examination and model fitting, known as "data snooping." Further, the small number of data points allows us to highlight dominant relations through plotting techniques. This approach is well known; see, for example, Frees (1996) and references cited there. The remaining portion, 5,675 taxpayers, is called the validation sample.

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[2] The database does contain a few "late" returns (for example, a late 1978 return may be included in the 1979 panel). We eliminated all returns with dates not matching the panel year.

[3] Because taxpayers typically pay preparation fees in the subsequent calendar year, preparation fees for 1987 (1988) returns, if disclosed, appear on the 1988 (1989) returns for each respective taxpayer. We lose one year of data (1989) because we use the fee disclosed on the 1989 tax return as the measure of 1988 fees.

TAX LIABILITY MODEL AND VARIABLE MEASUREMENT

As described in the previous section, we identify the demand factors of (1) tax savings, (2) time savings, and (3) uncertainty as the base elements of the multidimensional product provided by professional tax preparers. This section describes the estimation of a tax liability model using a panel data set that allows us to create measures of tax savings and uncertainty. The tax liability model is a one-way (individual) fixed-effects model of taxpayer tax liability that uses the first five years of our panel data. It estimates reported tax liability as a function of common variables identified in the literature, including a dummy variable and associated interaction variables for preparer impact. The preparer impact parameter estimates are then multiplied by the taxpayer's corresponding 1988 characteristics (natural log of total positive income, marital status, etc.) and summed, providing an estimate of the tax savings from using a preparer in 1988 for the binary choice and fee demand models. For each taxpayer, the standard deviation of their residuals from this model become our measure of historical uncertainty in tax liability for the binary choice and censored regression models.

Variable Choice

Appendix A details our choice of variables, where we largely follow the work of Long and Caudill (1987). It could be argued that tax liability could be perfectly predicted, as our database contains line-item tax return information. However, preparers have the opportunity to impact virtually every line item on a tax return. Our variables are selected because they appear consistently in prior research and are largely exogenous. Briefly, our variables are as follows: MS, HH, AGE, EMP, and PREP are indicator variables coded 1 for married, head-of-household, at least 65 years of age, self-employed, and paid preparer, respectively. DEPEND is the number of dependents. MR is the exogenous marginal tax rate measure (computed using TPI and the standard deduction, rather than using adjusted gross income and itemized deductions, both of which are more subject to preparer influence). TPI and TAX are the total positive income and tax liability as stated on the return in 1983 dollars, respectively.

Table 1 describes the basic taxpayer characteristics used in our analysis. Dichotomous variables indicate that over half the sample is married (MS) and approximately half the sample uses a paid preparer (PREP). Preparer use appears highest in 1986 and 1987, years straddling significant tax law change. Slightly less than 10 percent of the sample is 65 or older (AGE) in 1982. The presence of self-employment income (EMP) is also increasing over time.

The summary statistics for continuous variables indicate an increasing income trend, even after adjusting for inflation, as measured by total positive income (TPI). (We did the analysis in both real and nominal terms and the results we describe here are substantially the same.) Both the mean and median marginal tax rates (MR) are decreasing, although mean and median tax liabilities (TAX) are increasing. These results are consistent with congressional efforts to reduce rates and expand the tax base through broadening the definition of income and eliminating deductions in TRA 86.

Table 2 presents Pearson correlation coefficients for the tax liability model characteristics as well as some transformations of those characteristics. No single variable appears to be especially correlated with the use of a paid preparer (PREP).

Tax Liability Model

We estimate measures of tax savings and uncertainty from a one-way fixed-effects model predicting tax liability. We use the first five years, 1982–84 and 1986–87, to fit the model. The remaining year, 1988, is used to estimate our choice-based and fee models. For a detailed description of fixed-effects panel data models, see, for example, Hsiao (1986) and Baltagi (1995). The specification of our model is:

$$y_{it} = \begin{cases} \alpha_i + \lambda_{1t} + \lambda_{1t} + X_{it}\Gamma + \varepsilon_{it}\sigma_i & \text{self-prepared returns} \\ \alpha_i + \lambda_{1t} + \lambda_{1t} + \Delta_{PREP} + X_{it}(\Gamma + \Delta) + \varepsilon_{it}\sigma_i & \text{paid-preparer returns} \end{cases} \tag{1}$$

TABLE 1
DESCRIPTIVE STATISTICS
(n = 5,993)

Panel A: Means of Indicator Variables[a]

Year	MS	HH	AGE	EMP	PREP
1982	0.581	0.075	0.090	0.144	0.467
1983	0.589	0.079	0.101	0.154	0.482
1984	0.606	0.077	0.112	0.160	0.495
1986	0.622	0.080	0.136	0.166	0.538
1987	0.623	0.074	0.144	0.170	0.539
1988	0.631	0.073	0.158	0.177	0.532

Panel B: Summary Statistics for Other Variables[b]

Variable	Year	Mean	Median	Minimum	Maximum	Standard Deviation
DEPEND	1982	2.46	2	1	6	1.43
	1983	2.47	2	1	6	1.42
	1984	2.44	2	0	5	1.34
	1986	2.43	2	0	5	1.31
	1987	2.38	2	0	6	1.37
	1988	2.40	2	0	6	1.34
TPI (1983 dollars)	1982	26,354	20,933	1	591,415	27,049
	1983	27,119	21,286	1	828,712	28,971
	1984	28,656	23,019	1	856,303	29,827
	1986	29,818	22,606	1	1,201,963	41,228
	1987	32,431	24,032	1	6,493,820	93,125
	1988	33,891	24,282	1	4,358,864	74,849
MR	1982	24.70	23	0	50.0	12.37
	1983	23.44	23	0	50.0	11.29
	1984	23.77	23	0	50.0	10.72
	1986	23.06	23	0	50.0	11.68
	1987	20.89	15	0	38.5	9.94
	1988	19.52	15	0	33.0	8.38
TAX (1983 dollars)	1982	3,687	2,035	0	231,088	7,547
	1983	3,511	1,942	0	250,100	7,819
	1984	3,594	2,036	0	363,330	8,236
	1986	4,313	2,206	0	549,179	13,815
	1987	4,458	2,195	0	1,390,845	20,811
	1988	4,757	2,286	0	916,314	16,786

[a]MS, HH, AGE, EMP, and PREP are indicator variables coded 1 for married, head-of-household, at least 65 years of age, self-employed, and paid preparer, respectively.
[b]DEPEND is the number of dependents. MR is the exogenous marginal tax rate measure. TPI and TAX are the total positive income and tax liability as stated on the return in 1983 dollars, respectively.

TABLE 2
PEARSON CORRELATION COEFFICIENTS[a]

	LNTPI	LNTAX	PREP	EMP	TAX	MR	TPI	AGE	DEPEND	HH
LNTAX	0.72									
PREP	0.15	0.07								
EMP	0.06	−0.06	0.21							
TAX	0.34	0.27	0.07	0.21						
MR	0.84	0.73	0.14	0.04	0.34					
TPI	0.44	0.31	0.09	0.07	0.94	0.42				
AGE	−0.09	−0.08	0.12	−0.04	−0.00	−0.11	−0.03			
DEPEND	0.33	0.11	0.08	0.13	−0.00	0.17	0.09	−0.20		
HH	−0.09	−0.12	−0.05	−0.08	−0.05	−0.11	−0.06	−0.07	0.03	
MS	0.42	0.22	0.17	0.19	0.11	0.26	0.19	0.01	0.64	−0.36

[a]Correlations are based on a sample size of 29,665, corresponding to observations of five years (1982–84, 1986–87) for 5,933 individuals. TPI and TAX are the total positive income and tax liability as stated on the return in 1983 dollars, with LNTPI and LNTAX their respective natural logarithms, respectively. PREP, EMP, AGE, and HH are indicator variables coded 1 for presence of a paid preparer, self-employed, at least 65 years of age, and head-of-household, respectively. MR is the exogenous marginal tax rate measure. DEPEND is the number of dependents.

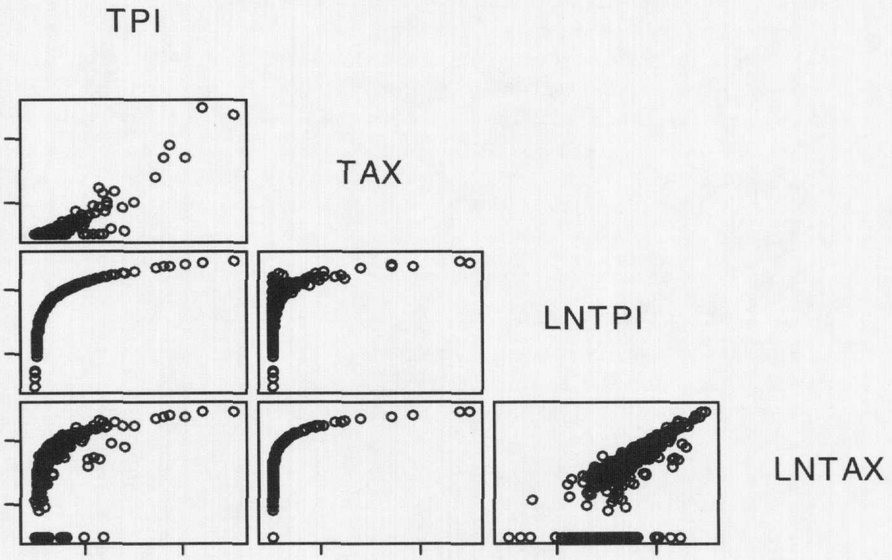
Here, y_{it} is the logarithm of the tax liability (LNTAX) for the ith taxpayer at time t, α_i is an individual specific intercept, X_{it} is a row vector of characteristics determining tax liability and Γ is the corresponding column vector of parameters. The list of characteristics that we use in X_{it} appears in Table 1 and Appendix A. From equation (1), we see that the difference in the expected logarithmic tax liability when using or not using a preparer is $\Delta_{prep} + X_{it}\Delta$. We use the parameter estimates of this expression applied to the taxpayer's 1988 characteristics (X_{it}, where t = 1988) to estimate the individual's 1988 tax savings generated by using a paid preparer.

The quantities λ_{1t} and λ_{2t} are time-specific intercepts that correspond to years 1986 and 1987, respectively. These two intercepts account for the effect of the 1986 Tax Reform Act. The noise term is assumed composed of an i.i.d. component, ε_{it}, and an individual-specific standard deviation parameter, σ_i. Through this term we allow the variability of y_{it}, Var $y_{it} = \sigma_i^2$, to differ by individual and thus, σ_i is a summary measure of an individual's uncertainty. We use estimates of σ_i to represent the individual's volatility of unexplained tax liability (after controlling for the effect of a paid preparer).

By estimating tax savings in this manner, the panel data set provides us with advantages that were not available to other researchers, such as Long and Caudill (1987). Through the individual-specific intercept estimates α_i, our one-way fixed-effects model controls for unmeasurable variables that may be correlated with included explanatory variables. Thus, for example, we did not need to include state-specific time invariant factors that are known to be important determinants (such as state tax rates, Long and Caudill 1993).

The fixed-effects modeling approach also avoids one source of potential endogeneity bias in the model, as described by Mundlak (1978); see also the discussion in Hsiao (1986, chapter 3.4). To illustrate, it may be that high levels of tax liability, y_{it}, affect preparer choice, an explanatory variable. However, the individual intercepts, α_i, capture time-invariant information in the response such as a consistently high rate of tax liability. Regarding the estimation, an individual intercept "sweeps-out" the time-series mean, so we are only comparing differences of the response from its mean, $y_{it} - \bar{y}_i$, to the corresponding differences for the explanatory variables. Further, by the above

FIGURE 1
SCATTERPLOT MATRIX OF TOTAL PERSONAL INCOME (TPI), TAX AND LOGARITHMIC TRANSFORMATIONS



These variables are used in the tax liability model and these data represent observations from the training sample. The scatter plot of TPI vs. TAX displays a nonlinear relationship. By transforming both TPI and TAX to a (natural) logarithmic scale, two linear relationships are apparent. For zero taxes paid, the slope is zero although for positive taxes paid, the slope is positive.

differencing of variables from their individual means, the panel data setup allows us to reduce the limited dependent variable bias encountered by the clustering of a variable at zero (in this case, tax liability) that occurs when looking at the data in a purely cross-sectional manner. (See the discussion of Figure 2 for further explanation.) We also investigated using a random-effects formulation for the model in equation (1), that is, assuming that α_i is a random variable. However, a Hausman test showed a significant difference between fixed and random effects estimates. (The Hausman test statistic was 530.4 with corresponding p-value = 0.0001.) We interpret this to mean that there is a substantial correlation between $\{\alpha_i\}$ and the explanatory characteristics in $\{X_{it}\}$ thus making the random effects specification inappropriate.

Model Identification

Figure 1 shows the relations between total positive income (TPI), tax liability (TAX) and their logarithmic transforms.[4] The plot in the upper left-hand panel shows a positive relation between TPI and TAX that was evident in our correlation Table 2. By comparing the plots in Figure 1, we see that the relation becomes much closer to a linear one by transforming each variable to a

[4] In this study, all "logarithmic" transformations are meant to imply that we add 1 to the variable before taking logs, that is, z becomes $\ln(1 + z)$ under a "logarithmic" transformation. This allows inclusion of values of z that are zero, for example, filers that pay zero tax in a year.

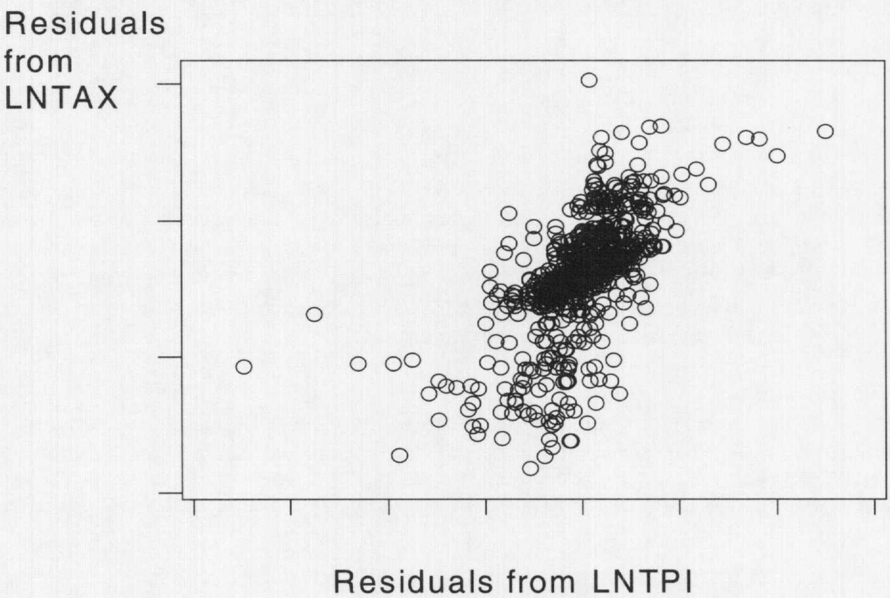
logarithmic scale (LNTPI and LNTAX, respectively). Further, the log scale plot clearly identifies the clustering of tax liability at zero, a feature of the data that causes difficulties of limited dependent variable bias. This difficulty was also noted by Long and Caudill (1987) who solved it using a Tobit analysis.

Figure 2 shows that a Tobit analysis is unnecessary in our panel-data context due to the individual-specific effects that we can control for through the intercept terms α_i. Figure 2 is an added variable plot of LNTAX and LNTPI; specifically, a plot of LNTAX minus its five-year individual-specific mean. An added variable plot, also called a partial regression plot, is a standard graphical device used in regression analysis. Its purpose is to view the relation between a response and an explanatory variable, after controlling for the linear effects of other explanatory variables. In this application, the other explanatory variables that we control for are the individual-specific intercept terms. Figure 2 shows that the addition of the individual-specific effects parameter eliminates the necessity for a Tobit analysis. Individual-specific effects may be estimated using panel data; however, they are unidentifiable using purely cross-sectional models.

Model Estimation

Estimation of the tax liability model's parameters (α_i, Γ, Δ_{prep}, and Δ) is done using ordinary (one-way fixed-effects) least squares as noted in equation (1). Table 3 presents the estimation results of the tax liability model with transformed variables. Estimated with the validation sample (all the data except for our 4 percent "training" sample), the model captures a substantial portion of the variation in the data. The adjusted R^2 is 79.7 percent. To illustrate that the individual-specific intercepts represent an important feature in capturing variation in taxpayer behavior, we fit the tax

FIGURE 2
ADDED VARIABLE PLOT OF TAX VS. TOTAL PERSONAL INCOME (TPI)



As in figure 1, both TAX and TPI have been converted to (natural) logarithmic scale. By also controlling for individual effects, the relation producing a zero slope for paying zero tax has been removed.

TABLE 3
TAX LIABILITY MODEL PARAMETER ESTIMATES[a]

Variable	Pooled Cross-Sectional		Individual Intercept Without Interactions		Individual Intercept	
	Parameter Estimates	t-statistic	Parameter Estimates	t-statistic	Parameter Estimates	t-statistic
MS	−0.190	−4.01	0.182	3.18	0.066	0.94
HH	−0.584	−10.19	0.003	0.04	−.057	−0.67
DEPEND	−0.132	−8.50	−.151	−8.23	−.146	−6.14
AGE	−0.011	−0.20	−.019	−0.28	0.169	1.87
LNTPI	1.138	38.04	0.658	32.20	0.683	23.93
MR	0.099	39.01	0.123	58.32	0.136	47.45
EMP	−0.393	−7.61	−.117	−2.78	−.018	−0.25
TIME = 1986	0.334	13.26	0.354	17.39	0.347	17.08
TIME = 1987	0.434	16.45	0.568	25.59	0.563	25.46
PREP	2.053	6.48	−.096	−3.05	0.843	2.71
MS*PREP	0.251	3.88			0.217	2.61
HH*PREP	0.374	4.38			0.104	0.99
DEPEND*PREP	−0.007	−0.31			−.010	−0.38
AGE*PREP	−0.250	−3.70			−.314	−3.28
LNTPI*PREP	−0.201	−5.06			−.052	−1.37
MR*PREP	−0.012	−3.64			−.023	−6.53
EMP*PREP	−0.378	−6.18			−.153	−1.96
INTERCEPT	−6.149	−26.20				
R^2	0.597		0.796		0.797	

[a]Estimates are based on the validation sample of 5,675 taxpayers filing tax returns in each of the five years 1982–84, 1986–87. MS, HH, AGE, EMP, TIME = 1986, TIME = 1987, and PREP are indicator variables, coded 1 for taxpayers who are married, head-of-household, at least 65 years of age, self employed, file in 1986, file in 1987, and use a paid preparer, respectively. DEPEND is the number of dependents. LNTPI is the natural logarithm of total positive income in 1983 dollars and MR is the exogenous marginal tax rate measure. Multiplicative variable names represent interaction terms. The dependent variable is the natural logarithm of reported tax liability.

liability model with a constant intercept (α). The resulting adjusted R^2 is only 59.7 percent, indicating that the individual-specific intercepts should be retained in the model. The change in the explanatory power of the individual intercept model with the interaction terms (R^2 = .797) and without the interaction terms (R^2 = .796) is small. However, we also perform a partial F-test (Chow test) to assess whether the interaction terms are important; the results show that they are. The parameters in the vector Γ differ significantly from zero. See Table 3 for details.

Table 3 shows that preparer and four of the seven preparer-related coefficients are significant predictors of tax liability. In contrast to Long and Caudill (1987), PREP has a positive coefficient, indicating that the presence of a preparer, controlling for other items, is associated with a higher tax liability. We conjecture that this is an indication of an "enforcement" function. The interaction term MS*PREP also has a positive coefficient. The terms with negative coefficients are AGE*PREP, MR*PREP, and EMP*PREP. Thus, preparers reduce the tax liabilities of taxpayers who are older, have a higher tax rate or are self-employed. This is consistent with the assertion that preparers save taxes in specific areas of the tax return. The preparer interactions with dependents, head-of-household, and income are not significant. Table 3 also shows that the two-time dummy variables that correspond to λ_{1t} and λ_{2t} (for years 1986 and 1987, respectively) are statistically significant. These two variables are introduced to control for the effects of TRA86.

Measure of Tax Savings

The estimated tax liability model allows us to compute two measures that are input variables in the binary choice and fee demand models. These two variables are (1) the tax savings associated with preparer use for 1988 and (2) a measure of the taxpayer's attitude toward uncertainty. The tax savings measure is computed similarly to Long and Caudill (1987); we use the parameter estimates ($\hat{\Delta}$) displayed in Table 3 and the 1988 characteristics to compute estimates $\hat{\Delta}_{PREP} + X_{it}\hat{\Delta}$ for each taxpayer, labeled TAXSAVE.

Measure of Uncertainty

The taxpayer's purchase of risk protection is composed of two pieces: (1) the inherent risk that the IRS will select the return for audit and propose an adjustment, and (2) the taxpayer's attitude toward risk. Neither of these constructs can be directly measured from our data. However, we propose the following proxies.

The inherent risk measure, UNCERTAIN, is computed as the standard deviation of unexplained tax liability measured over the five periods 1982, 1983, 1984, 1986, 1987. Here, the unexplained tax liability is the residual from the tax liability model. The interpretation is that by controlling for both the individual-specific effects and the impact of the explanatory variables (including that of the paid preparer), known determinants of tax liability are captured. The remainder we think of as the "unexplained" tax liability. The individual-specific standard deviations capture the size of the "typical" absolute unexplained tax liability and this size is a measure of an individual's attitude toward uncertainty regarding tax liability. Individuals with smaller standard deviations have historically enjoyed less variability in their tax liability and conversely for individuals with larger standard deviations. It is possible to use alternative estimates of σ_i, such as the average absolute residual. However, as described in Carroll and Ruppert (1988), an advantage of residual standard deviations is that they provide information about the standard deviations even if the mean regression function is incorrectly specified, whereas average absolute residuals may be misleading.

We postulate that, *ceteris paribus*, tax returns with highly variable tax liabilities over time have, on average, higher inherent risk of audit. Such taxpayers may have numerous and varied sources of income and deductions. As a result, their taxable income streams are likely to involve more special tax rules and opportunities for tax-planning strategies. Variability as a measure of risk has support in the areas of financial accounting, insurance, finance, etc., and intuitive appeal from a tax perspective. However, no empirical tax research directly links variability with increased risk of an inaccurate tax return, or increased risk of audit. We conjecture that this direct lack of support results from the unavailability of time-series data on both tax audit risk and evasion. Anecdotal evidence does exist. Averages for itemized deductions are published annually in the popular press, suggesting that taxpayers should be especially certain of their deductions if they stray too far from published means. Although the IRS discriminant function is confidential, it is not unreasonable to postulate that means and standard deviations in line-item TCMP data might have some effect on audit selection. Carroll (1992) studies diaries kept by taxpayers during filing season, and notes comments that include taxpayer concern with staying comparable to various reference groups. These groups include the taxpayer's prior returns, friends, and other reference frames. Comments indicate concern with deviation from prior year's tax liability, refund, and various line items (such as charitable contributions). Some taxpayers even noted that they practiced evasion to change their reported line-item amounts to be comparable with their chosen reference frames. Thus, taxpayers and tax agencies may view returns that vary from reference frames as more likely to be incorrect or subject to audit.

Descriptive Statistics for Explanatory Variables in the Choice and Utilization Models

In summary, TAXSAVE represents the estimated amount of (logarithmic) tax an individual could expect to save by using a preparer. UNCERTAIN represents the time-series standard deviation of an individual's tax liability that is not directly attributable to wealth and other individual characteristics. We use this measure to quantify the volatility, or uncertainty, of an individual's tax position over time. The third input variable, opportunity cost (OPCOST), is measured by computing an hourly wage rate based on total personal income and applying it to the IRS-reported estimates of the time it takes to read the instructions and complete each form filed. Christian et al. (1993) introduced this measure.

Descriptive statistics of TAXSAVE, UNCERTAIN, and OPCOST appear in Table 4. For the full validation sample, the mean and medians of TAXSAVE for self-prepared returns are smaller than those for paid-preparer returns. This supports the notion that paid preparers save tax dollars for their higher income clients. There is most likely some rational selection process occurring here and one would not expect paid preparers to be able to save tax dollars on the majority of self-prepared returns. If that were true, the self-prepared returns would employ paid preparers. The mean value of UNCERTAIN is, as anticipated, larger for the paid-preparer returns than self-prepared returns. However, the median value of UNCERTAIN is not, and there is considerable variability between taxpayers in both preparation modes.

TABLE 4
1988 VALIDATION SAMPLE DESCRIPTIVE STATISTICS
BINARY CHOICE AND FEE DEMAND MODEL VARIABLES

Variable[a]	Mean	Median	Minimum	Maximum	Standard Deviation
Full Validation Sample, n = 5,675					
UNCERTAIN	0.912	0.469	0.037	6.242	0.954
TAXSAVE	0.006	0.026	−1.261	0.920	0.259
OPCOST	4.089	4.126	−6.221	9.722	1.165
TSAVCOST	0.218	0.088	−2.355	7.530	1.118
Self-Prepared Sample (PREP = 0), n = 2,650					
UNCERTAIN	0.897	0.478	0.037	6.242	0.887
TAXSAVE	−0.016	0.004	−1.261	0.813	0.242
OPCOST	3.780	3.912	−5.969	9.722	1.142
TSAVCOST	0.091	0.014	−2.073	7.530	0.943
Paid Preparer Sample (PREP = 1), n = 3,025					
UNCERTAIN	0.925	0.461	0.047	6.073	1.008
TAXSAVE	0.026	0.051	−1.175	0.920	0.271
OPCOST	4.360	4.339	−6.221	9.582	1.116
TSAVCOST	0.330	0.222	−2.355	7.344	1.241
Taxpayers With FEE > 0, n = 691					
UNCERTAIN	0.760	0.439	0.059	6.073	0.919
TAXSAVE	0.131	0.135	−1.175	0.893	0.248
OPCOST	5.000	4.855	−6.211	9.582	1.046
TSAVCOST	0.827	0.674	−1.889	7.344	1.364
FEE	4.926	4.836	2.398	9.018	0.930

[a]UNCERTAIN represents the residual standard deviation of unexplained tax liability. TAXSAVE is the estimated impact a paid preparer has on tax liability, in natural logarithmic dollars. For the median savings equal to 0.026, we interpret this to mean that the "typical" tax savings is 2.6 percent. For example, when comparing two taxpayers who have identical characteristics, we expect the taxpayer who does use a paid preparer to spend 2.6 percent less in taxes than one who does not. OPCOST is the estimated opportunity cost of self-preparing the tax return, in natural logarithmic dollars. TSAVCOST is the interaction of TAXSAVE and OPCOST. FEE is the natural logarithm of the related tax preparation fee.

To understand the relations between our three independent variables, UNCERTAIN, TAXSAVE, and OPCOST, and our dependent variable, preparer type (PREP) we use the training sample of 258 taxpayers. Figure 3 plots the relations of UNCERTAIN, TAXSAVE, and OPCOST by preparer type for the training sample. The plot indicates that taxpayers with high TAXSAVE and OPCOST tend to use preparers, suggesting the need for an interaction term between these two variables. We call this interaction term TSAVCOST = TAXSAVE*OPCOST. Descriptive statistics, based on the remainder of the data, for this interaction variable appear in Table 4.

BINARY CHOICE DEMAND MODEL

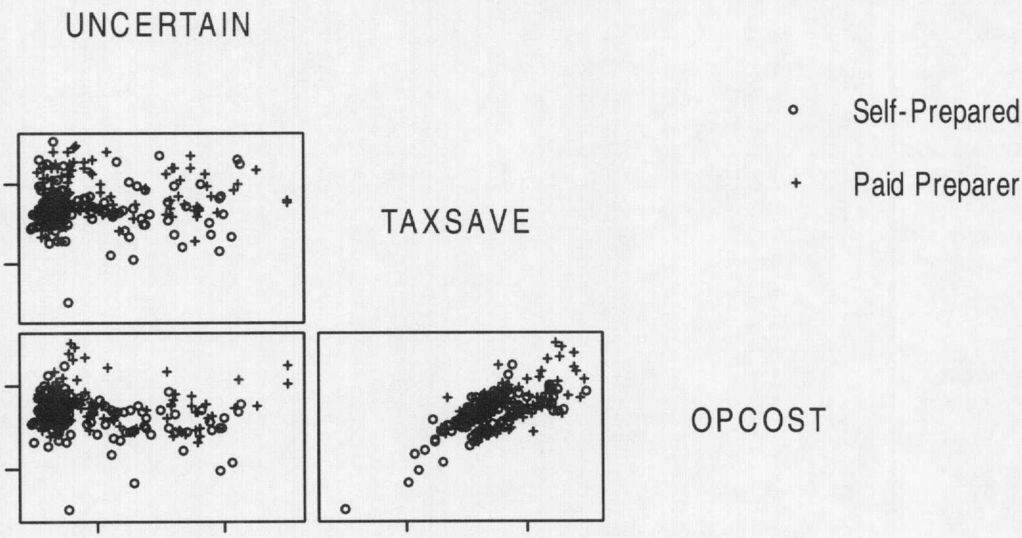
We estimate a model of preparer choice using cross-sectional logistic regression and 1988 tax returns for the validation sample of 5,675 taxpayers. The purpose of this analysis is twofold. First, it serves as a conduit between prior research on preparer choice and our examination of fee determinants. Second, our binary choice model contains refinements over previous work in that we are the first to empirically specify the uncertainty variable from archival data. Further, both the tax savings and uncertainty measures are computed from panel data outside the estimation period, reducing potential endogeneity bias.

Theoretically, our binary choice demand model is defined as follows:

preparer choice
= f(uncertainty, tax savings, time savings, interaction of tax savings and time savings)

where the dependent variable, preparer choice is coded 1 for a paid preparer return and zero

FIGURE 3
SCATTERPLOT MATRIX OF INSURANCE, TAX SAVINGS (TAXSAVE) AND OPPORTUNITY COSTS (OPCOST), BY LEVEL OF PREPARER



These variables are used in the logistic and censored regression models and these data represent observations from the training sample. This figure displays the relationships among the variables and shows, for example that no collinearity is evident. Further, from the TAXSAVE vs. OPCOST panel, we see that taxpayers with high levels of TAXSAVE and OPCOST are likely to use a preparer. This suggests using the interaction term, TAXSAVE * OPCOST = TSAVCOST.

otherwise. Uncertainty (UNCERTAIN) is the residual standard deviation of unexplained tax liability. Tax savings (TAXSAVE) is the estimated impact of a paid preparer on tax liability. Both of these measures are developed as described in the Table 3 tax liability model. Time savings (OPCOST) is the estimated opportunity cost of self-preparing the tax return and TSAVCOST is the interaction of TAXSAVE and OPCOST.

Table 5 presents the estimation results. Consistent with the theory, we find, for the validation sample, higher opportunity costs are associated with selecting a paid preparer. UNCERTAIN is also positive, in contrast to Collins et al. (1990) who found no significance in their anxiety measure. Although the Table 4 descriptive statistics show TAXSAVE to be positive for paid preparer returns, the TAXSAVE coefficients in this model are negative. Somewhat mitigating this result, however, is the positive interaction term TSAVCOST, which indicates that high-opportunity cost taxpayers purchase tax savings. This result is consistent with Lin (1993). We also ran the model without the UNCERTAIN variable and found that the results are similar to the fitted model that includes UNCERTAIN. This indicates that the model results of tax and time savings are not being driven by the introduction of the uncertainty measure.

Although not reported in Table 5, we also explored the possibility that taxpayers with different income levels purchase a different mix of products from preparers. Segregating taxpayers by 1988 total positive income (TPI), these panels estimate the choice model for taxpayers above and below the median and those in the center two quartiles. The results for lower TPI taxpayers indicate that they purchase time savings and uncertainty protection. The positive and significant coefficient for TSAVCOST indicates that tax savings may motivate preparer use, but only with taxpayers having higher opportunity cost (i.e., higher income, more complicated returns, or both). The results for the center two quartiles show the coefficient for UNCERTAIN is insignificant and the TAXSAVE coefficient is negative and much larger than any other partition of the data. Observations with income in the top half of the validation sample behave in a manner somewhat more consistent with theory. The positive sign on the coefficient for UNCERTAIN is approaching significance and the negative coefficient for TAXSAVE is the weakest of the groups.

TABLE 5
BINARY CHOICE DEMAND MODEL PARAMETER ESTIMATES[a]

	INTERCEPT	UNCERTAIN	TAXSAVE	OPCOST	TSAVCOST
Model With UNCERTAIN Variable:					
Parameter	−2.1750	0.141	−1.646	0.525	0.357
p-value	0.0001	0.000	0.000	0.000	0.000
−2 Log Likelihood = 7,422.38					
Model Without UNCERTAIN Variable:					
Parameter	−1.9480	Not Applicable	−1.767	0.500	0.384
p-value	0.0001	Not Applicable	0.000	0.000	0.000
−2 Log Likelihood = 7,442.26					

[a]Based on the validation sample variables summarized in Table 4 (n = 5,675). The dependent variable is preparation mode (self-prepared = 0, paid preparer = 1). UNCERTAIN represents the residual standard deviation of unexplained tax liability. TAXSAVE is the estimated impact a paid preparer has on tax liability. OPCOST is the estimated opportunity cost of self-preparing the tax return. TSAVCOST is the interaction of TAXSAVE and OPCOST. A measure of overall model adequacy is minus twice the log-likelihood (−2 Log Likelihood). Fitting the model without any explanatory variables yields −2 Log Likelihood = 7,842.42. Likelihood ratio test procedures establish that the variables in each model are jointly as well as individually statistically significant.

In summary, the overall results are consistent with employing tax preparers to provide protection from uncertainty and to save time, but not to save taxes. The results also are consistent with the notion of different packages of goods being purchased by different income levels.

FEE DEMAND MODEL

In this model, we examine fees by identifying their relations with time savings, tax savings, and uncertainty. Theoretically, the model is defined as follows:

preparer fee
= f(uncertainty, tax savings, time savings, interaction of tax savings and time savings).

The model is cross-sectional and is estimated on 1988 tax returns using the same independent variables as the binary choice demand model. The dependent variable is the natural logarithm of the associated preparer fee which, if available, is reported on the taxpayer's 1989 tax return.[5]

The estimation is further complicated by three factors. First, the variable FEE is available only if a taxpayer uses a paid preparer. Second, preparation fees are deductible only if a taxpayer's deductions are itemized and the sum of the fees plus other miscellaneous deductions is in excess of 2 percent of adjusted gross income. Because of these two reasons, the data are censored. Third, upon inspection of the data, we discover that, even though they need not be reported and cannot be deducted, preparer fees are reported for a significant portion of the data. We conjecture that this may be due to a marketing practice of some tax preparation firms recording their fees on a taxpayer's form to symbolize their attention to detail.[6] Thus, a complex maximum likelihood is required to model fees as a function of tax savings, time savings, and uncertainty, yet at the same time adjusting for censorship due to the tax code and the random censorship.

Censored Regression Model

The development of the likelihood function is as follows. When available, we use the tax preparer's FEE as a measure of the tax preparer's value. Of course, the variable FEE is available only if a taxpayer uses a paid preparer, and even then may be censored. For a taxpayer who uses a tax preparer, let y_1^* be the true, potentially unobserved, fee for a preparer's services. This variable will appear on Schedule A of Form 1040 if it is observed. Further, let y_2^* denote the true, other miscellaneous deductions that may appear on Schedule A of Form 1040. In order to qualify for a deduction, and thus appear on the tax form, the sum of these two variables must exceed 2 percent of adjusted gross income (AGI). That is, we observe the preparer's fee if:

$$y_1^* + y_2^* > (0.02)\ \text{AGI}. \qquad (2)$$

However, when equation (2) does not hold, the preparer's fee may still appear on the tax form. This is true despite the fact that the taxpayer receives no deduction for the preparer's fee.

We use a random censoring variable (W) to indicate that fee is censored when equation (2) does not hold. This is because, although a significant portion of our data turns out to be uncensored even when equation (2) does not hold, we could detect no other patterns of censorship. In this sense, the fee variable is *partially* censored.

For the censored regression model, let X_F denote the row vector of explanatory variables associated with fee (y_1^*). Similarly, use Z for a row vector of explanatory variables associated with other miscellaneous deductions (y_2^*). As described above, we use X_F = (1, TAXSAVE, OPCOST, UNCERTAIN, TSAVCOST) for the determinants of fee. Because y_2^* is an ancillary variable, used only to calibrate our censoring mechanism in equation (2), we report only models using Z = 1.

[5] It is also possible that the reported fee may relate to years other than 1988 or that some portion of the fee may be deducted in another section of the return (such as fees related to self-employment income). We are unable to identify such phenomena in our data.

[6] Conference participants suggested that this may also be the result of computer software packages documenting preparer input, even if no deduction is allowed.

Further investigations using alternative specifications of Z did not seem to improve the estimation results that follow.

To complete the censored regression model specification, we assume that both type of (true) miscellaneous deductions follow a linear model:

$$\log y_1^* = X_F \beta + e_F \tag{3}$$

and

$$\log y_2^* = Z \gamma + e_O. \tag{4}$$

Here, β and γ are vectors of parameters. Further e_F and e_O are assumed to be mean zero, normally distributed error terms with variances σ_F^2 and σ_O^2, respectively, with correlation ρ. Because we condition on preparer usage, we have that $y_1^* > 0$. We also assume that $y_2^* > 0$ conditional on preparer usage.

As described above, for each taxpayer that uses a tax preparer, we have available X_F, Z, and AGI. For the fee and other miscellaneous deductions, we observe:

$$(y_1,y_2) = \begin{cases} y_1^*,y_2^* & \text{if } C = 0 \\ y_1^*,0 & \text{if } C = 1 \text{ and } W = 0 \\ 0,0 & \text{if } C = W = 1. \end{cases}$$

Here, $\{C = 0\}$ means that equation (2) holds; in other words, $\{C = 1\}$ means that the sum of fee and other miscellaneous deductions does not exceed 2 percent of adjusted gross income. We also use $p_w = \text{Prob}(W = 0)$ to denote the probability of our random censoring mechanism.

Denote the parameters of our model as $\theta = (\beta', \gamma', \sigma_F, \sigma_O, \rho, p_w)'$. We estimate this vector of parameters using maximum likelihood, assuming multivariate normality of the errors in equations (3) and (4). We assume independence among individuals so that our sampling satisfies standard regularity conditions (see, for example, Serfling 1980). Thus, we can get asymptotic normality and subsequent standard errors for the estimates. Appendix B describes the development of the likelihood function.

Estimation Results

Table 6 provides the results of the estimation procedure for our validation sample. The parameter estimate of the probability of censorship (p_w) is large and very statistically significant (t-ratio = 131.254). This is not surprising in that only 12 percent of our taxpayers reported paying professional fees (even though over half of them used a paid preparer). The estimation yields significant parameter estimates for all four variables of interest: UNCERTAIN, TAXSAVE, OPCOST, and TSAVCOST.

The parameter estimate of TAXSAVE is positive and significant. We interpret this coefficient to mean that taxpayers who enjoy more tax savings from the use of preparers pay greater fees. Similar results are found for OPCOST, indicating that taxpayers with higher opportunity costs are willing to pay higher fees. Because FEE, TAXSAVE, and OPCOST are all logarithmic transformations, the parameter estimates represent proportional changes and the economic interpretation of these results is as follows. Suppose that we compare two taxpayers with otherwise identical characteristics with values for TAXSAVE and OPCOST at the Table 4 mean values for the paid preparer sample (.026 and 4.36, respectively), yet one taxpayer would enjoy 1 percent larger tax savings from the use of a preparer. This implies that this taxpayer would pay .74 percent more in fees, (accounting for both the direct effect and the interaction term). Similarly, a 1 percent increase in opportunity cost would relate to a .83 percent increase in fees. The interaction TSAVCOST is negative and significant, but the parameter estimate is smaller in magnitude than either TAXSAVE or OPCOST. The interaction reduces fees, but less than either variable alone increases them. It is not surprising that the market price for both tax and time saving is not the sum of the two pieces. In some sense, taxpayers get a "bargain price" from the combination of these two products. In addition, we estimated the model with and without the UNCERTAIN variable. In this way, our results concerning tax and time savings are robust with respect to the uncertainty measure.

TABLE 6
FEE DEMAND MODEL PARAMETER ESTIMATES[a]

	Model With UNCERTAIN Variable			Model Without UNCERTAIN Variable	
Variable		Parameter Estimate	t-statistic	Parameter Estimate	t-statistic
INTERCEPT_FEE	(β_0)	0.596	2.399	0.361	1.374
UNCERTAIN	(β_1)	−0.150	−4.009	Not Applicable	
TAXSAVE	(β_2)	2.536	4.384	2.776	4.743
OPCOST	(β_3)	0.746	12.914	0.765	12.796
TSAVCOST	(β_4)	−0.391	−3.259	−0.441	−3.602
INTERCEPT_MSC	(γ_0)	0.366	1.171	0.390	1.341
SIGMA_FEE	(σ_F)	1.060	38.849	1.070	38.653
SIGMA_MSC	(σ_0)	4.261	21.541	4.252	22.850
RHO	(ρ)	0.443	12.495	0.458	13.016
PROBCENSORSHIP	(p_w)	0.863	131.254	0.863	131.244

[a]Based on the validation sample variables summarized in Table 4. All observations have PREP = 1. The dependent variable is the natural log of the 1988 preparation fee as disclosed on the 1989 tax return. UNCERTAIN represents the residual standard deviation of unexplained tax liability. TAXSAVE is the estimated impact a paid preparer has on tax liability. OPCOST is the estimated opportunity cost of self-preparing the tax return. TSAVCOST is the interaction of TAXSAVE and OPCOST. INTERCEPT_MSC is the intercept parameter estimate for other miscellaneous deductions. SIGMA_FEE and SIGMA_MSC are the respective standard deviations of the error terms for the fee and other miscellaneous deductions models, with correlation RHO. PROBCENSORSHIP is the censorship correction parameter.

The UNCERTAIN coefficient is negative in sign, and significant. Taxpayers with highly variable "unexplained" tax liabilities buy tax assistance (Table 5), but the purchase is not reflected in the price of the basket of goods they purchase, i.e., the fee. One could argue that taxpayers with highly variable unexplained tax liabilities are either better negotiators than others, or have a different price for uncertainty. It is also possible that UNCERTAIN is capturing constructs other than just risk.

However, this result is also consistent with preparers providing uncertainty protection, but failing to include its price in their fee structure. Note that while Pratt and Stice (1994) find uncertainty being priced in the audit services area, we find little evidence of this in the tax services area. One possible explanation for this is data driven. Pratt and Stice (1994) use experimental, not archival, data. Another explanation is that the need to price audit risk is much greater for audit services than for tax services. Although the majority of litigation against accountants is tax related, the truly devastating financial losses occur in audit services. Even if this is true, it does not indicate that tax service risk should not be priced (for it appears to be purchased), but only that firms have not yet devised a method of pricing it.

As with the choice model, we also investigated the relation of fees to the basket of services purchased that varied over income levels (not reported in Table 6). Only opportunity cost is reflected in the fees paid by taxpayers with income below the median. This is consistent with the difficulty to either provide or document significant tax savings for low-income taxpayers. Taxpayers in the center half of the income distribution appear to have some uncertainty premium attached to their fees. However, evidence from the choice model shows that this group purchases the least amount of uncertainty protection of any group.

CONCLUSIONS

This study describes demand components for professional tax preparation services, and how they map into the pricing structure. It is the first study to incorporate uncertainty into both models of preparer choice and fee determination. The mapping is an important issue first, because of conflicting evidence on the efficiency of paid tax preparers and second, because the tax preparer profession has never overtly assumed an insurance function, except perhaps in the case of catastrophic losses. With increasing malpractice claims and penalties, the insurance function can no longer be ignored.

From a policy perspective, product pricing should impound product-demand factors. The combination of our binary choice model, which provides insights as to why taxpayers are purchasing preparation services, and the partially censored regression model, which indicates whether these product-demand components are impounded in the pricing structure, provides us the relevant evidence.

The overall results of the study indicate that taxpayers choose paid preparers for reasons associated with uncertainty and time savings. Fees, however, reflect a different product mix and are associated with tax savings and time savings, but not uncertainty. The results of both models vary somewhat by income level. From a policy perspective, the results suggest that pricing structures for professional tax preparation services may need to be adjusted to more closely reflect the services provided.

APPENDIX A
VARIABLE DEFINITIONS[7]

Demand Models

Dependent Variables

FEE = the amount charged to prepare the tax return. It is censored because the fee is only deductible when it exceeds 2 percent of AGI and the taxpayer itemizes. The deductible fee relates to the prior year.

PREP = a variable indicating the presence of a paid preparer.

Independent Variables

TAXSAVE = consistent with Long and Caudill (1987), tax saving is the estimated impact paid preparers have on tax liability.

OPCOST = consistent with Christian et al. (1993), time saving is measured as opportunity cost. Opportunity cost is computed by multiplying the taxpayer's average hourly wage rate by the estimated amount of time spent on the tax return. The average hourly wage is TPI divided by the number of working hours in a typical year (2040 for single taxpayers and 4080 for married taxpayers). Estimated time spent on the tax return is the sum of the IRS estimated learning, preparing, and assembling time as reported in the instructions of each form used.

UNCERTAIN = as discussed in Section V, uncertainty is the residual standard deviation of unexplained tax liability, computed over a five-year period.

Tax Liability Model

Dependent Variable

TAX = the tax liability on the return.

[7] All continuous variables are in real dollars.

Independent Variables—Demographic Characteristics

MS = an indicator variable of the taxpayer's marital status, coded one if the taxpayer is married and zero otherwise.
HH = an indicator variable, one if the taxpayer is a head of household and zero otherwise.
DEPEND = the number of dependents claimed by the taxpayer.
AGE = an indicator coded one for age 65 or over and zero otherwise.

Independent Variables—Economic Characteristics

TPI = the sum of all positive income line items on the return.
MR = exogenous marginal tax rate. It is computed on TPI less exemptions and the standard deduction.
EMP = an indicator variable, one if Schedule C or F is present and zero otherwise. Self-employed taxpayers have greater need for professional assistance to reduce the reporting risks of doing business.
PREP = a variable indicating the presence of a paid preparer.

APPENDIX B
CENSORED REGRESSION LIKELIHOOD FUNCTION

To develop the likelihood function, we consider three cases: (1) both the fee and other miscellaneous deductions are uncensored ($C = W = 0$), (2) the sum of fee and other miscellaneous deductions is less than 2 percent of adjusted gross income yet the fee is observed ($C = 1$, $W = 0$), and (3) the sum of fee and other miscellaneous deductions is less than 2 percent of adjusted gross income and the fee is not observed ($C = W = 1$). We handle each case in turn.

B.1 Case 1—Fee and Other Miscellaneous Deductions are Uncensored

For this portion of the likelihood, both variables are continuous outcomes. We use the bivariate normality and equations (2) and (3) to directly write the logarithmic joint density of $\log y_1^*$ and $\log y_2^*$ as:

$$\log g(w_1,w_2) = -\log\left(2\pi\sigma_F\sigma_O\sqrt{1-\rho^2}\right) - \frac{1}{2(1-\rho^2)}\left[\left(\frac{w_1 - X'\beta}{\sigma_F}\right)^2 - 2\rho\left(\frac{w_1 - X'\beta}{\sigma_F}\right)\left(\frac{w_2 - Z'\gamma}{\sigma_O}\right) + \left(\frac{w_2 - Z'\gamma}{\sigma_O}\right)^2\right].$$

See, for example, Hogg and Craig (1978, 117).

Using a change of variable technique (with a Jacobian transformation), this yields the logarithmic joint density of y_1^* and y_2^* as:

$$\log f(y_1^*,y_2^*) = -\log y_1^* - \log y_2^* - \log(2\pi\sigma_F\sigma_O\sqrt{1-\rho^2}) - \frac{1}{2(1-\rho^2)}\left[\left(\frac{\log y_1^* - X'\beta}{\sigma_F}\right)^2 - 2\rho\left(\frac{\log y_1^* - X'\beta}{\sigma_F}\right)\left(\frac{\log y_2^* - Z'\gamma}{\sigma_O}\right) + \left(\frac{\log y_2^* - Z'\gamma}{\sigma_O}\right)^2\right]. \tag{B.1}$$

B.2 Case 2—Fee Plus Other Miscellaneous Deductions is Less than Deductible, Yet Fee is Observed

Here, for simplicity, we use $D = (0.02)$ AGI as our deductible. For this case, we have the fee as a continuous variable although other miscellaneous deductions is discrete (at $y_2 = 0$). Thus, we examine:

$$\frac{\partial}{\partial t}\text{Prob}(y_1 = y_1^* \le t, y_2 = 0) = \frac{\partial}{\partial t}\text{Prob}(y_1^* \le t, y_1^* + y_2^* \le D, W = 0)$$

$$= p_W \frac{\partial}{\partial t}\text{Prob}(y_1^* \le \min(t, D - y_2^*))$$

$$= p_W \frac{\partial}{\partial t}\text{Prob}(\log y_1^* \le \min(\log t, \log(D - y_2^*))). \qquad \text{(B.2)}$$

Here, we assume that $t < D$. Because $\log y_2^*$ is normally distributed, we may express the density of y_2^* as:

$$f_2(x) = (x\ \sigma_O)^{-1}\ \varphi((\log x - Z'\ \gamma)/\sigma_O),$$

where $\varphi(.)$ is the standard normal density function. That is, y_2^* is said to have a lognormal distribution. Using this expression in equation (B.2), we get:

$$p_W \frac{\partial}{\partial t}\text{Prob}(\log y_1^* \le \min(\log t, \log(D - y_2^*)))$$

$$= p_W \frac{\partial}{\partial t}\left(\int_0^{D-t} \text{Prob}(\log y_1^* \le \log t) f_2(x)\, dx + \int_{D-t}^{D} \text{Prob}(\log y_1^* \le \log (D - x)) f_2(x)\, dx\right)$$

$$= p_W \frac{\partial}{\partial t}\left(\text{Prob}(\log y_1^* \le \log t)\ \text{Prob}(\log y_2^* \le \log(D - t))\right.$$

$$\left. + \int_{D-t}^{D} \text{Prob}(\log y_1^* \le \log(D - x)) f_2(x)\, dx\right)$$

$$= p_W \left(\frac{\partial}{\partial t}\left(\Phi\left(\frac{\log t - X'\beta}{\sigma_F}\right)\Phi\left(\frac{\log(D - t) - Z'\gamma}{\sigma_O}\right)\right) + \text{Prob}(\log y_1^* \le \log t) f_2(D - t)\right)$$

$$= p_W \left(\frac{1}{t\ \sigma_F}\ \phi\left(\frac{\log t - X'\beta}{\sigma_F}\right)\ \Phi\left(\frac{\log(D - t) - Z'\gamma}{\sigma_O}\right)\right.$$

$$- \frac{1}{(D - t)\sigma_O}\ \phi\left(\frac{\log(D - t) - Z'\gamma}{\sigma_O}\right)\ \Phi\left(\frac{\log t - X'\beta}{\sigma_F}\right)$$

$$\left. + \frac{1}{(D - t)\sigma_O}\ \Phi\left(\frac{\log t - X'\beta}{\sigma_F}\right)\ \phi\left(\frac{\log(D - t) - Z'\gamma}{\sigma_O}\right)\right)$$

$$= \frac{p_W}{t\ \sigma_F}\ \varphi\left(\frac{\log t - X'\beta}{\sigma_F}\right)\ \Phi\left(\frac{\log(D - t) - Z'\gamma}{\sigma_O}\right). \qquad \text{(B.3)}$$

Here, $\Phi(.)$ is the standard normal cumulative distribution function.

B.3 Case 3—Fee Plus Other Miscellaneous Deductions is Less than Deductible and Fee is Not Observed

The calculation of the likelihood with both variables censored has no continuous components. We begin by noting that the probability of censorship can be expressed as:

$$\text{Prob}(C = W = 1) = (1 - p_W)\ \text{Prob}(y_1^* + y_2^* \le D)$$

$$= (1 - p_W)\ \text{Prob}(\exp(X'\beta + \varepsilon_F) + \exp(Z'\gamma + \varepsilon_O) \le D) \qquad \text{(B.4)}$$

Thus, the probability of censorship is the convolution of two lognormal random variables. To compute this quantity, we first use conditioning. Using standard results in mathematical statistics, we have that:

$$\varepsilon_F|(\varepsilon_O = \varepsilon_O^*) \sim N\left(\frac{\sigma_F}{\sigma_O}\varepsilon_O^*, \sigma_F^2(1-\rho^2)\right).$$

See, for example, Hogg and Craig (1978, 119). Using this, equation (B.4) and the law of iterated expectations, we have:

$$\begin{aligned}\text{Prob}(C = W = 1) &= (1 - p_W)\, E\,(\text{Prob}(\exp(X'\beta + \varepsilon_F) \leq D - \exp(Z'\gamma + \varepsilon_O^*)|(\varepsilon_O = \varepsilon_O^*)))\\ &= (1 - p_W)\, E\,(\text{Prob}(\varepsilon_F \leq \log(D - \exp(Z'\gamma + \varepsilon_O^*)) - X'\beta|(\varepsilon_O = \varepsilon_O^*)))\\ &= (1 - p_W) E\, \Phi\left(\frac{\log(D - \exp(Z'\gamma + \varepsilon_O^*)) - X'\beta - \rho\frac{\sigma_F}{\sigma_O}\varepsilon_O^*}{\sigma_F\sqrt{1-\rho^2}}\right). \qquad \text{(B.5)}\end{aligned}$$

Because $\varepsilon_O \sim N(0, \sigma_O^2)$, the probability of censoring in equation (B.5) may be computed using either simulation or numerical integration techniques. In this paper, we computed this probability as:

$$\text{Prob}(C = W = 1) = \frac{(1 - p_w)}{\text{nsim}} \sum_{i=1}^{\text{nsim}} \Phi\left(\frac{\log(D - \exp(Z'\gamma + \varepsilon_{Oi}^*)) - X'\beta - \rho\frac{\sigma_F}{\sigma_O}\varepsilon_{Oi}^*}{\sigma_F\sqrt{1-\rho^2}}\right) \qquad \text{(B.6)}$$

where $\{\varepsilon_{Oi}, i = 1,\ldots,\text{nsim}\}$ is a random sample of normal random variables with mean zero and variance σ_0^2. Here, after experimentation with accuracy of the function, we used the number of simulations equal to nsim = 100.

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