DETERMINANTS OF TAX PREPARER USAGE: EVIDENCE FROM PANEL DATA

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Abstract *- This study provides new evidence on the factors associated with using tax return preparers from a balanced panel of microlevel tax return data for 1982–4. The results of fixed-effects logit models that control for unobservable differences across individuals indicate that (1) the time-cost of return preparation has a positive albeit small impact on preparer use, (2) the type of tax return filed and employment status are important determinants of preparer use, and (3) the effect of income and marginal tax rate on preparer use in models that control for complexity and source of income is unclear.*

Currently, almost half of all federal individual income tax returns, and an even greater proportion of complex returns, are prepared by professional tax return preparers at a cost that exceeds seven billion dollars annually (IRS, 1992; Blumenthal and Slemrod, 1992). In addition to this widespread involvement, preparers provide a more cost-effective conduit for IRS communication efforts and can also be more easily monitored than taxpayers because they are a much smaller group. Despite these important institutional realities, very little is known about the motivations, circumstances, and events that affect taxpayers' use of preparers. Citing this significant omission from extant research, the National Academy of Sciences' Panel on Taxpayer Compliance Research (Roth, Scholz, and Witte, 1989, p. 178) concluded the following:

> From a policy perspective, greater knowledge about the relationships between tax practitioners and taxpayer compliance could offer one of the most promising areas for improving compliance.

Researchers have only recently begun to theoretically and empirically examine the influence of preparers in the tax system generally and on taxpayer compliance in particular. A few analytical studies have developed microeconomic models of taxpayer compliance that specifically consider the role of preparers (*e.g.*, Beck, Davis, and Jung, 1989; Scotchmer, 1989; Reinganum and Wilde, 1990). Empirical studies using audited data to examine the compliance levels of paid-prepared and self-prepared

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returns have yielded ambiguous results. Klepper and Nagin (1989) found preparers have a mixed effect on compliance—they appear to be rule enforcers but ambiguity exploiters. Erard (1990) found that the magnitude but not frequency of noncompliance on paid-prepared returns is significantly higher. However, return preparation mode arguably is endogenous in tax compliance models, because reporting decisions may affect preparation mode choice (Erard, 1990; Udell, 1991). Therefore, examining the effect of preparers on compliance also requires modeling taxpayers' preparation mode choice.[1]

Previous research on the determinants of preparer usage, though sparse, has provided useful insights. Studies using survey data have found certain taxpayer demographics and attitudes to be important factors. Specifically, Slemrod and Sorum (1984) found expenditure on professional tax assistance by Minnesota taxpayers to be positively associated with older, unmarried, self-employed, and less educated taxpayers. Collins, Milliron, and Toy (1990) found that factors associated with demand for preparer services in Oklahoma and Pennsylvania depended on the taxpayer's objective in hiring a preparer. While income and age were positively associated with preparer usage among those with a tax minimization objective, social responsibility and complexity were positively associated with usage for those with an objective of filing a correct return. Low tax knowledge was positively associated with usage for both groups. Neither audit anxiety nor effort minimization (time savings) appeared to be associated with preparer use in either group.

Prior studies have also used tax return data to examine the determinants of preparer usage. Based on unaudited data from 1983 tax returns, Long and Caudill (1987) found preparer usage positively related to marginal tax rate, income level, source of income, complexity, and being self-employed. While the probability of using a preparer also was significantly higher for taxpayers age 65 or over, the effect of other demographic variables depended on itemization status. Similarly, based on audited data from the 1982 TCMP, Erard (1990) found preparer usage to be positively associated with complexity, age, marital status, and high-profile occupation (chief executive, elected official, *etc.*). However, unlike Long and Caudill, Erard did not find that income and marginal tax rate were associated with preparer usage.

Both groups of studies are limited in scope and the inferences they allow one to draw on the factors associated with preparer use. While the results of survey research are subject to the possibility of response bias (*e.g.*, Slemrod and Sorum, 1984; Slemrod, 1989), the results of tax return data-based studies potentially suffer from an omitted variables bias. This is because the many taxpayer characteristics that survey research suggests are likely determinants of preparer usage (*e.g.*, education and sense of social responsibility) are likely to be correlated with the included variables (*e.g.*, income and employment status) in cross-sectional studies. Panel data from tax returns offer a promising way to deal with both problems.

The purpose of this study is to provide new evidence on the determinants of paid-preparer usage from a panel of tax returns filed by a group of taxpayers over a three-year period (1982–4). The analysis is based on Chamberlain's (1980) conditional logit model, which controls for the unobservable heterogeneity in individual characteristics that are constant across time. Hence, the bias from omitting these variables is reduced or eliminated. Also, the panel used in this study spans statutory tax rate changes that introduced variation in marginal tax rate independent of changes in income. This improves the ability to identify tax rate effects on preparer usage separate from income effects.

This study also provides new evidence on the separate effects of complexity, source of income, and opportunity costs of self-preparation as factors influencing preparer usage. Although survey research indicates that saving time and effort is not an important objective for using preparers (Yankelovich, Skelly, and White, 1984; IRS, 1988; Collins *et al.*, 1990), the opportunity cost of taxpayer time ("time-cost") has never been formally separated from complexity in previous studies using tax return data. Finally, unlike previous preparer usage studies, we control for the type of tax return form (1040, 1040A, or 1040EZ) filed by the taxpayer. Apart from the frequency of preparer usage varying greatly by return type, we expect that the factors associated with preparer use, especially with regard to complexity, also differ by return type. Hence, this analysis should enhance our ability to more clearly identify the separate influences of complexity, time-costs, and source of income on preparer usage.

Our principal findings are as follows. First, there is statistically significant evidence of individual heterogeneity, which suggests that cross-sectional estimates of preparation mode choice suffer from omitted variables bias. Second, while time-cost is significant and positively associated with preparer usage, its marginal effect appears to be small (even a $100 increase in the time-cost of self-preparation increases the probability of preparer usage by only 4.3 percent). Third, the probability of using preparers is significantly higher (by 31 percent) for self-employed taxpayers and increases with complexity (by 5.5 percent for each additional form or schedule attached to the return). Finally, we do not observe a consistent association between marginal tax rate and preparer usage, although income and tax rate remain strongly correlated in the panel.

The rest of this paper is organized as follows. The next section provides a brief discussion of the relative merits of panel data. The third section discusses our empirical procedures, including the model tested in this study, the data and sample selection procedures used, and the estimation technique employed. The fourth section presents our results, and the fifth section provides a conclusion.

THE RELATIVE ADVANTAGES OF PANEL DATA

In addition to providing larger numbers of observations, panel data have many advantages over cross-sectional or time-series data.[2] First, panel data allow control for unobserved variables that are time invariant. It is well known that if these omitted variables are correlated with the included explanatory variables, standard estimation methods yield biased parameter estimates. Panel data overcome this problem if the omitted variables are individual-specific characteristics, because they tend not to vary over time, especially over short periods. Second, as is also well known, identifying the independent effects of tax rate and income on taxpayers' behavioral responses to taxation is highly problematic. Panel data that span years in which tax rate schedules are changed can potentially overcome this identification problem by providing variation in tax rates that is independent of changes in income. In this study, our three-year panel of 1982–4 tax returns includes the effect of tax rate cuts phased in under The Economic Recovery Tax Act of 1981 (ERTA).[3] Finally, panel data allow investigation of the dynamics of behavioral response in that one can possibly identify factors that have an immediate or lagged effect or how expectations about future changes may affect taxpayer response. However, short panels, such as that used in this study, limit one's ability to confidently infer these effects.

In a typical panel (including most tax return panels), there are a large number of cross-sectional units but only a few time

periods. Recent econometric work has developed many estimation techniques particularly suited to analyzing such short and wide panel data sets [see Chamberlain (1984) and Hsiao (1986) for reviews]. These techniques focus on cross-sectional variation or individual heterogeneity while assuming constant slope parameters across individuals. An important issue that faces the investigator is whether these individual effects should be treated as fixed or random. Because the inferences drawn from a fixed-effects model are conditional on the effects in the sample (*i.e.*, are not generalizable outside the sample), it has been argued that the individual effects should always be treated as random (Mundlak, 1978). However, a critical assumption of the random-effects model is that the individual effects are uncorrelated with the explanatory variables, which is usually hard to justify. If such correlation exists, then the random-effects estimation produces biased results, whereas the fixed-effects model does not because it treats the individual effects as just another parameter to be estimated. In this study, we expect that the unobserved individual-specific effects (*e.g.*, taxpayer's education, level of tax knowledge, sense of social responsibility, *etc.*) are likely to be correlated with the explanatory variables we can observe, such as income and complexity. Some of these, such as education, are likely correlates of income holding tax rate constant. Hence, we use a fixed-effects estimation technique described later.

Despite the numerous advantages of both panel data and the associated econometric techniques discussed above, there are also some disadvantages. For example, construction of a panel requires repeat observations on the same individual. In the case of tax return panels, individuals may escape inclusion for a number of reasons, such as change in marital status, death, decline in income below the minimum threshold for filing, or late filing of the tax return. Such attrition may induce a survivorship bias in the observations for which multiple years' data is available in the panel. Second, because the estimation techniques for panel data focus on the changes in behavior and the changes in the explanatory variables of interest, the signal-to-noise ratio in the data may decrease. Thus, caution must be exercised in interpreting the results, especially for variables with modest changes over time.

EMPIRICAL PROCEDURES

Model and Variable Definitions

A conceptual model of the demand for tax preparer services based on prior research may be expressed as follows:

tax preparer usage = *f*
(socioeconomic and demographic characteristics, risk aversion, employment status, complexity, time-cost, tax knowledge, education, and social responsibility).

Given the information available in tax returns, the dependent variable in this study is coded 1 if a paid preparer's signature appears on the return, and 0 otherwise. Measurement error may be introduced if taxpayers purchase professional tax services yet prepare their own returns, taxpayers use preparers only in certain years and self-prepare following their advice in subsequent years, or if preparers do not sign the return even though failure to do so is illegal (Roth *et al.*, 1989, p. 173). The extent of this problem is unknown, and, in any case, we have no reason to believe that it materially impacts the results.

With regard to the independent variables, data on tax knowledge, education, and social responsibility are not available from tax returns. However, as discussed before, these taxpayer characteristics are likely to be relatively constant over short time pe-

riods and thus controlled for in fixed-effects models. Proxies used in this study for the remaining conceptual variables are defined below.

TPI: total positive income, *i.e.*, sum of all positive income line items on the return, divided by $10,000 and stated in 1983 dollars.

MTR: marginal tax rate calculated as the statutory federal tax rate on predeflated TPI minus the allowance for personal exemptions.

MS: dummy variable for married (joint or separate) filing status.

DEPS: number of dependents.

AGE65: dummy variable for presence of at least one additional exemption for age 65 or over.

EMP: dummy variable for presence of Schedule C (business) or F (farm) income.[4]

FORMS: number of the following forms attached to the return—1116, 2106, 2119, 2439, 2441, 3468, 3903, 4136, 4137, 4255, 4684, 4797, 4835, 4868, 4970, 4972, 5329, 5405, 5544, 5695, 5884, 6251, 6765, and Schedule R.

SCHS: number of the following separate schedules (defined below) attached to the return—SCHA, SCHB, SCHD, SCHE, SCHG, and SCHW.

SCHA: dummy variable for presence of Schedule A (itemized deductions).

SCHB: dummy variable for presence of Schedule B (interest or dividends greater than $400 or all-savers interest) income.

SCHD: dummy variable for presence of Schedule D (net capital gain less loss) income.

SCHE: dummy variable for presence of Schedule E (rent, royalty, or partnerships) income.

SCHG: dummy variable for presence of Schedule G (income averaging).

SCHW: dummy variable for presence of Schedule W ("two-wage earner") deduction.

COST: reporting burden in hours multiplied by an after-tax wage rate.[5]

1040: dummy variable indicating the filing of tax return Form 1040.

1040EZ: dummy variable indicating the filing of tax return Form 1040EZ.

The variable TPI is included to examine the influence of socioeconomic factors on preparer use. Absent data on wage rates and educational level, TPI can also be viewed as a surrogate for the opportunity cost of preparing one's own return and would be expected to have a positive effect on preparer use (Long and Caudill, 1987). Finally, TPI also serves as a proxy for risk aversion. If risk aversion is decreasing in income as is commonly assumed, then TPI could have a negative effect on preparer use. Given the different roles of income, interpretation of the TPI coefficient estimates is complicated.

The variable MTR is included as a measure of the value of tax preparers' services and is expected to positively impact preparer use. This is because reduction in tax liability is more valuable as the tax rate rises. This effect is likely to be more pronounced for itemizers, because they can deduct tax preparation fees. The definition of MTR used here follows Long and Caudill (1987) and measures the tax savings associated with the "first dollar" of itemized or standard deductions, adjustments to income, or tax losses.[6]

The variables MS, DEPS, and AGE65 are included to examine demographic influences

on the preparer use decision. The variable EMP is included to investigate the effect of employment status. Self-employed taxpayers generally have been found to be more likely to use professional return preparers in part because (1) they tend to have more complicated returns and (2) the accountant handling the financial affairs of the business routinely prepares the owner's tax return as well (Long and Caudill, 1987, p. 37).

The variables FORMS and SCHS are included to capture the additional complexity created by having to attach supplemental forms and schedules to the tax return. It also takes additional effort to prepare these forms and schedules. Both reasons suggest that these variables should positively impact preparer use. Note that Schedules C and F are not included in SCHS, because they comprise the EMP variable. We also estimate models including a vector of dummy variables for each schedule included in SCHS. The income schedules (SCHB, SCHD, and SCHE) can be viewed as reflecting different sources of income, which provide greater planning opportunities as well as increase the complexity of the return. Thus, these variables are expected to have a positive effect on preparer use.

The variable COST is included to capture separately the saved time-costs of using a preparer. It is calculated from yearly IRS estimates of the total time associated with filing each tax form (*i.e.*, the reporting burden) and a return-specific surrogate for wage rate that takes into account differences in taxpayers' value of time.[7] Because the value of preparer services increases with the time-costs, we expect COST to have a positive effect on preparer use.

Finally, we also include two dummy variables (1040 and 1040EZ) for the type of tax return form filed by the taxpayer, with 1040A being the base scenario. These variables are included because the frequency of preparer usage varies greatly by return type and the motivations underlying preparer usage are likely to be quite different between taxpayers filing the different return forms. Return type also may represent the initial "trigger" of complexity. We expect the use of Form 1040 to positively impact preparer use and the use of Form 1040EZ to have a negative impact.

Data and Sample Selection

Data are from the Statistics of Income Panel of Individual Returns (SOI Panel), which is a part of the Ernst and Young/University of Michigan Tax Research Database. The SOI Panel is a subset of the SOI Individual Model File and represents a simple random sample of individual income tax returns filed each year. Although data currently are available for tax years 1979–88, information on return preparation mode is available only in 1982–4 and 1986–8.

To perform the panel data analysis in this study, we pooled cross-sectional and time-series data for 1982–4 and obtained a balanced panel; *i.e.*, our panel contains returns of only those taxpayers who are included in the SOI Panel in each of the three years.[8] From the balanced panel, we first eliminated a small number of returns erroneously included in the SOI Panel by the IRS.[9] Returns were also deleted if the tax year did not match the panel file year (*e.g.*, a 1982 tax return that is in the 1983 SOI Panel). Next, returns that were not self-prepared or paid-prepared in any of the three years were eliminated.[10] This resulted in a final sample size of 7,686 taxpayer identification numbers (IDs) that had tax return information for each of the three years, for a total of 23,058 observations.

Table 1 presents descriptive statistics, including pairwise correlations, for selected variables from the 1982–4 panel and from a 1983 cross section that is more comparable to Long and Caudill (1987). As Table 1 indicates, 47.3 percent of the returns in

TABLE 1

VARIABLE DESCRIPTIVE STATISTICS FOR ALL TAXPAYERS IN THE 1982–4 BALANCED PANEL (n = 23,058; 7,686 in each year) AND IN THE 1983 CROSS SECTION (n = 18,570)[a]

Variable[c]	Mean	Standard Deviation	Pearson Correlation Coefficient[b]										
			TPI	MTR	MS	DEPS	AGE65	EMP	FORMS	SCHS	COST	1040	1040EZ
PREP	0.473	0.499	0.17	0.17	0.19	0.07	0.13	0.23	0.21	0.33	0.16	0.42	−0.34
	0.454	0.498	0.13	0.20	0.21	0.07	0.14	0.23	0.20	0.34	0.12	0.44	−0.19
TPI (in $10,000)	2.497	2.790		0.72	0.34	0.16	−0.04	0.11	0.37	0.55	0.78	0.32	−0.23
	2.288	3.963		0.53	0.26	0.12	−0.00	0.10	0.28	0.42	0.87	0.24	−0.13
MTR (percent)	24.0	11.1			0.33	0.11	−0.05	0.07	0.33	0.62	0.36	0.43	−0.29
	21.8	11.5			0.38	0.13	−0.01	0.10	0.34	0.66	0.28	0.46	−0.24
MS	0.548	0.498				0.36	0.02	0.21	0.24	0.46	0.17	0.37	−0.43
	0.492	0.500				0.37	0.04	0.22	0.25	0.47	0.14	0.38	−0.06
DEPS	0.844	1.209					−0.23	0.08	0.16	0.14	0.07	0.11	−0.27
	0.794	1.206					−0.22	0.09	0.18	0.13	0.06	0.11	0.13
AGE65	0.118	0.322						−0.04	−0.05	0.11	−0.01	0.19	−0.14
	0.116	0.320						−0.03	−0.06	0.16	0.01	0.21	−0.11
EMP	0.145	0.352							0.25	0.21	0.25	0.28	−0.16
	0.131	0.337							0.24	0.22	0.19	0.30	−0.20
FORMS	0.389	0.726								0.42	0.47	0.33	−0.21
	0.313	0.643								0.38	0.35	0.31	−0.18
SCHS	1.45	1.36									0.40	0.62	−0.41
	1.23	1.30									0.31	0.62	−0.36
COST ($)	64.4	217.7										0.20	−0.11
	55.6	271.6										0.15	−0.10
1040	0.683	0.465											−0.57
	0.633	0.482											−0.67
1040EZ	0.130	0.336											
	0.204	0.403											

[a]The upper number is for balanced panel, and the lower number is for the 1983 cross-sectional data.

[b]All correlation coefficients are significantly different from zero at the 0.01 level, except for ρ'[AGE, TPI] (p = 0.6614), ρ'[AGE, MTR] (p = 0.1094), and ρ'[AGE, COST] (p = 0.1630) for the 1983 data and ρ'[AGE, COST] (p = 0.0951) for the balanced panel.

[c]See text for variable definitions.

the balanced panel are paid-prepared, and the average taxpayer reports TPI of about $25,000 and faces a marginal tax rate of 24 percent. About 55 percent of the taxpayers are married, nearly 12 percent claim the additional age exemption for 65 years or over, and over 14 percent report income from self-employment. The average taxpayer takes about 4.9 hours to meet the filing requirements of the return with an estimated after-tax time-cost of $64. Compared to the cross-sectional data, returns in the panel data have higher income and tax rates, more forms, schedules, and time-cost, and a larger proportion of returns are from married taxpayers.

We also observe a strong correlation between TPI and MTR, both in the 1982–4 panel ($\rho = 0.72$) and in the 1983 cross section ($\rho = 0.53$). We were surprised to find the higher correlation in the panel, so we calculated sample correlations for the other years in the panel (not reported in Table 1). For the cross sections in 1982 and 1984, the correlations are 0.41 and 0.60, respectively. However, if the cross sections are limited to include only those returns that are in the 1982–4 balanced panel, the correlations are 0.73, 0.73, and 0.71 for the same three years. This apparently reflects the greater homogeneity of returns that appear in all three years, which dominates the added variation of MTR independent of income that was introduced during the period by ERTA.

Estimation

Although covariance analysis in conjunction with panel data is a well-known econometric technique to control for individual differences, its use is not straightforward when the dependent variable is categorical. If the number of cross-sectional units in the panel is large, say thousands, the number of unknown parameters that must be estimated becomes intractable, because in a nonlinear model, it is not possible to sweep away the individual differences by taking deviations from the individual-specific means. In addition, because the number of time-series observations for a given cross-sectional unit is typically small in most panel data, obtaining maximum likelihood estimates is problematic (Greene 1990, p. 687). Chamberlain (1980) has developed a fixed-effects conditional logit model for panel data that overcomes these problems and produces unbiased estimates of the slope coefficients.[11]

Given that our dependent variable is a binary indicator of preparation mode choice, our panel data analysis is based on the Chamberlain model. However, it is necessary to test the null hypothesis of homogeneity of intercepts (*i.e.*, the equality of individual-specific effects). Hausman's (1978) specification test, which is based on a χ^2 statistic, provides an appropriate test of this hypothesis. If the null cannot be rejected, both Chamberlain's conditional maximum likelihood (CML) estimator and the usual maximum likelihood (ML) estimator for a pooled logit are consistent, but the CML estimator is inefficient because it fails to use the homogeneity restriction. If there is heterogeneity, the ML estimator is inconsistent, while the CML estimator is consistent and efficient.

RESULTS

The results of the logit regression analysis are presented in Tables 2 and 3, with the parameter estimates in the first row and, in parentheses, the two-tailed *p*-values of the related asymptotic *t*-statistics in the second row. The tables also include the likelihood ratio (LR) chi-square statistics, which test the null hypothesis that all coefficients are equal to zero, and the Hausman χ^2 statistic discussed above.

The Table 2 Logit Regression Results

Table 2 presents both 1983 cross-sectional and 1982–4 panel data estimates of four models. Following Long and Caudill (1987), Model 1 examines the effect of income,

marginal tax rate, taxpayer demographics, and employment status on preparer usage; Model 2 adds the tax complexity variables (FORMS and SCHS); and Model 3 replaces the variable SCHS by a vector of dummy variables (SCHA, SCHB, SCHD, SCHE, SCHG, and SCHW) indicating the presence of a particular schedule. Model 4 is the counterpart of Model 3 but estimated only for the subsample of itemizers.[12]

The cross-sectional results in Panel A indicate that the probability of preparer use is significantly higher for taxpayers who are married or older and increases with the number of dependents (although among itemizers it is lower for married taxpayers and decreases with the number of dependents). The probability is also higher if the taxpayer is self-employed and increases with complexity. This evidence is generally consistent with prior research and, especially, with Long and Caudill (1987).

Unlike Long and Caudill, however, the influence of income and tax rate on preparer use is unclear. Whereas TPI is negative in Models 2 and 3, MTR is positive in Model 1 but negative in Model 4. These results are suggestive of multicollinearity and the inability to separately identify the effects of TPI and MTR on preparer usage. The differences in the results may also be explained by differences in the data used in the two studies: whereas Long and Caudill use a large stratified sample, our simple random sample (although a proper subset of theirs) is much smaller.

As with the cross-sectional models, the diagnostics in Panel B indicate that the panel data models have good overall fit (the LR statistics are significant at $p < 0.01$ for all models).[13] However, based on the Hausman χ^2 statistics, the null hypothesis of homogeneity of intercepts is rejected at the 0.01 level in all models. As discussed before, this implies that control for individual-specific effects is necessary and that, therefore, the cross-sectional results in Panel A may be biased.

Although a detailed analysis of the panel data results is included with the Table 3 results below, the following observations from the panel data results in Panel B of Table 2 regarding the individual explanatory variables are noteworthy. First, once FORMS and SCHS are included in the model, neither TPI nor MTR is significant. Second, the demographic variables undergo several changes (*e.g.*, DEPS and AGE65 are generally insignificant; for itemizers, MS and AGE65 remain significant, but the sign on their coefficients is reversed). Finally, for the significant variables in both Panels A and B (*i.e.*, EMP, FORMS, SCHS, and the individual schedules), the coefficients and marginal effects in Panel B are larger than in Panel A. For example, the Panel B coefficient of EMP in Models 3 and 4 is about 1.7 with a marginal effect of 0.42 compared with the Panel A coefficient of about 1.07 with a marginal effect of 0.27.[14] Thus, the cross-sectional models appear to underestimate the effects of these variables on preparer usage.

The Table 3 Logit Regression Results

Table 3 presents the main results of this study based on the 1982–4 panel data set. Models 1a–4a are the counterparts of Models 1–4 in Panel B of Table 2, augmented with the two return-type dummies and the variable COST. The LR and Hausman statistics are significant at the 0.01 level in all models indicating good overall fit and the need to control for individual-specific effects.

The results indicate that both the type of tax return filed and the time-cost of tax preparation are important determinants of preparer usage, with the coefficients significant in the predicted direction in all models. The coefficients also exhibit a high degree of stability across the models. Based on marginal effects, however, the return type dummies are clearly more im-

TABLE 2
LOGIT REGRESSION RESULTS OF PAID TAX PREPARER USAGE
(TWO-TAILED *p*-VALUES OF ASYMPTOTIC *t*-STATISTICS IN PARENTHESES)

	Panel A *Models for 1983 Cross Section*				Panel B Models for 1982–4 Balanced Panel[a]			
	All Returns			Itemized	All Returns			Itemized
Variables	1	2	3	4	1	2	3	4
TPI	0.0119	−0.0108	−0.0120	0.0149	0.2333	−0.0267	−0.0224	0.0165
	(0.2081)	(0.0293)	(0.0174)	(0.1704)	(0.0026)	(0.6890)	(0.7392)	(0.8386)
MTR	0.0272	−0.0011	−0.0020	−0.0185	0.0129	0.0170	0.0132	−0.0315
	(0.0000)	(0.5774)	(0.3292)	(0.0000)	(0.2165)	(0.0879)	(0.1944)	(0.1070)
MS	0.3861	0.1082	0.2404	−0.1671	0.5753	0.2486	0.4411	1.0425
	(0.0000)	(0.0052)	(0.0000)	(0.0192)	(0.0023)	(0.2068)	(0.0437)	(0.0430)
DEPS	0.0647	0.0562	0.0481	−0.0512	−0.0477	−0.0539	−0.0595	−0.4617
	(0.0000)	(0.0001)	(0.0013)	(0.0205)	(0.5567)	(0.5127)	(0.4700)	(0.0077)
AGE65	1.0371	0.7816	0.7389	0.4074	0.6673	0.1896	0.1894	−1.1047
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0859)	(0.6369)	(0.6406)	(0.0585)
EMP	1.3188	1.0835	1.0615	0.6072	1.8196	1.6964	1.7010	1.4038
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FORMS		0.2891	0.2936	0.1706		0.4316	0.4163	0.1709
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.1178)
SCHS		0.4542				0.5499		
		(0.0000)				(0.0000)		

TABLE 2 (continued)

SCHA			0.5998				0.8543	
			(0.0000)				(0.0000)	
SCHB			0.3795	0.1005			0.3598	0.2906
			(0.0000)	(0.0856)			(0.0012)	(0.0450)
SCHD			0.2096	0.2185			0.5620	0.6409
			(0.0010)	(0.0048)			(0.0017)	(0.0069)
SCHE			0.8052	0.7029			0.8408	0.8229
			(0.0000)	(0.0000)			(0.0005)	(0.0153)
SCHG			0.4772	0.4854			0.7924	0.5448
			(0.0000)	(0.0000)			(0.0001)	(0.0293)
SCHW			0.1081	0.1878			0.2526	0.0925
			(0.0256)	(0.0031)			(0.1070)	(0.7396)
INTERCEPT	−1.3406	−1.1038	−1.1024	0.5574				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
Hausman χ^2					19.59	37.15	43.70	28.62
					(0.01)	(0.01)	(0.01)	(0.01)
LR χ^2	2,293.1	3,117.9	3,231.7	430.95	164.98	324.98	337.58	70.79
$p(\chi^2)$	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
n		18,570		6,905		23,058		7,932
Percent Paid-Prepared		45.4		61.7		47.3		61.2

[a]These results are based on Chamberlain's (1980) fixed-effects conditional likelihood estimator.

TABLE 3
ADDITIONAL LOGIT REGRESSION RESULTS OF PAID TAX PREPARER USAGE FOR THE 1982–4 BALANCED PANEL[a]
(TWO-TAILED p-VALUES OF ASYMPTOTIC t-STATISTICS IN PARENTHESES)

	All Returns			Item'd
Variables	1a	2a	3a	4a
TPI	−0.0636	−0.0860	−0.0786	−0.1189
	(0.4604)	(0.2754)	(0.3204)	(0.2480)
MTR	0.0189	0.0162	0.0130	−0.0202
	(0.1028)	(0.1452)	(0.2549)	(0.3201)
MS	0.1614	−0.0288	0.0303	1.1750
	(0.4560)	(0.8969)	(0.8997)	(0.0238)
DEPS	−0.1789	−0.1729	−0.1713	−0.4594
	(0.0347)	(0.0438)	(0.0464)	(0.0083)
AGE65	0.2545	0.0357	−0.0174	−0.9976
	(0.5242)	(0.9296)	(0.9662)	(0.0900)
EMP	1.1317	1.2054	1.2413	1.2256
	(0.0000)	(0.0000)	(0.0000)	(0.0004)
FORMS		0.2245	0.2203	0.0431
		(0.0066)	(0.0079)	(0.7255)
SCHS		0.3063		
		(0.0000)		
SCHA			0.1788	
			(0.2528)	
SCHB			0.2412	0.2800
			(0.0320)	(0.0537)
SCHD			0.4412	0.5367
			(0.0146)	(0.0268)
SCHE			0.6678	0.7015
			(0.0062)	(0.0423)
SCHG			0.5857	0.5028
			(0.0035)	(0.0477)
SCHW			0.2249	0.0983
			(0.1637)	(0.7243)
1040	1.584	1.3749	1.3943	
	(0.0000)	(0.0000)	(0.0000)	
1040EZ	−2.6018	−2.5833	−2.5876	
	(0.0000)	(0.0000)	(0.0000)	
COST	0.0043	0.0020	0.0017	0.0025
	(0.0000)	(0.0271)	(0.0550)	(0.0284)
Hausman χ^2	36.12	49.26	53.93	30.36
	(0.01)	(0.01)	(0.01)	(0.01)
LR χ^2	623.98	657.18	663.98	76.40
$p(\chi^2)$	(0.01)	(0.01)	(0.01)	(0.01)
n		23,058		7,932
Percent paid-Prepared		47.3		61.2

[a]These results are based on Chamberlain's (1980) fixed-effects conditional likelihood estimator.

portant than COST. On average, having to file a 1040 rather than a 1040A increases the probability of using a preparer by 34 percent, whereas having to file a 1040EZ rather than a 1040A reduces that probability by 64 percent. In contrast, increasing COST by $100 increases the probability of preparer usage by only 4.3 percent.

To examine whether COST represents just another measure of complexity, Model 2a is estimated including FORMS, SCHS, and the return-type dummies in addition to COST. The coefficients of all these variables are significant and positive as predicted. These results suggest that the variable COST may indeed reflect the time value of return preparation as intended. This result differs from the survey research that found

time savings was not an important determinant of preparer usage (Yankelovich *et al.*, 1984; IRS, 1988; Collins *et al.*, 1990).

To provide evidence on the separate effects of time-cost, complexity, and source of income on preparer usage, Model 3a is estimated with the vector of dummies for each separate schedule instead of the variable SCHS. The results show that all of the income schedules (B, D, and E) have a positive impact on preparer use. Based on marginal effects, Schedule E appears to have the largest effect—its presence increases the probability of preparer use by 15 percent. Apart from simply the additional complexity created by these income sources, a potential explanation for these results is that nonwage income typically provides greater planning opportunities that could make preparer use more beneficial.

Among the other schedules, the income averaging schedule (SCHG) is associated with increased preparer usage (its marginal effect is about 15 percent).[15] Apart from complexity, SCHG could also be capturing changed circumstances faced by a taxpayer that usually cause more uncertainty and the need for professional help. Alternatively, the increase in income of taxpayers who use SCHG also may make them better able to afford a paid preparer's services. Among the results for the other schedules, the most notable change is that Schedule A is rendered insignificant.

With regard to the other explanatory variables, EMP continues to have a strong positive influence on preparer usage: being self-employed increases the probability of using a preparer by about 30 percent. This could be the result of either the additional complexity associated with being self-employed or the small, if any, additional cost arising from having the accountant handling the bookkeeping and other similar functions of the business preparing the owner's tax returns.

Among the demographic variables, MS and AGE65 generally are not significant. These results could in part be due to insufficient variation in these variables over time for a given taxpayer, on which the panel data estimates are dependent.[16] However, DEPS is consistently significant and negative, and the marginal effect indicates that increasing one dependent reduces the probability of using a preparer by 4.3 percent. This result contrasts with Long and Caudill (1987), who find a positive effect of the number of dependents on preparer usage. Our results suggest that as the number of dependents increases, taxpayers are unwilling or unable to spend resources on tax preparation. The results are also consistent with the argument that additional reduction in taxable income arising from the increase in the number of dependents decreases taxpayers' incentive to engage preparers to further reduce their income. Finally, if the number of dependents is viewed as a proxy for the age of nonelderly taxpayers, our results are also consistent with Slemrod and Sorum's (1984) finding that paid-preparer usage rises with the age of the nonelderly. This is because we would expect the number of dependents to decline with age.[17]

Last, TPI and MTR are not significant in any Table 3 model. Because identifying the separate effects of TPI and MTR on preparer usage is difficult, we also tested the joint hypothesis that both coefficients are zero using a chi-square statistic, which was not significant at conventional levels (χ^2 = 2.4). Given the high correlation between the two variables in the panel data, we also estimated the full model without MTR, recognizing that TPI would then capture the combined effect of both variables. However, TPI was insignificant and results for the other variables were unchanged.[18]

Sensitivity Analysis. Although survey studies show that audit anxiety is not a determinant of preparer use (*e.g.*, Collins *et al.*, 1990), it has been argued that perceptions

of audit risk may also affect the decision to engage a preparer (Dubin *et al.*, 1992). Absent requisite data on taxpayer perceptions, however, these studies have used aggregated district-level audit rates calculated from the IRS Commissioner's Annual Report (IRS, 1982–4). Apart from significant conceptual problems associated with using this measure, there is little empirical support for its use. While Erard (1990) found no effect, Dubin *et al.* (1992) found that it increases the demand for "practitioners" but decreases the demand for "national tax services." We also estimated our models including IRS audit rate.[19] The coefficient of audit rate was not significant, and the other coefficients were unchanged and hence not presented here.

To test the possibility that the propensity to use a preparer may vary over time, the panel data models were also estimated with year dummies. The coefficients of these dummies were not significant, and the results for the other variables were unchanged. Finally, to test whether the tax return type dummies interact with the other explanatory variables, we estimated the full model separately for the subsample of 1040 returns. The results were identical to those of the full model, except that the coefficient on marital status was significant and positive.

Summary and Conclusions

Although almost half of all United States taxpayers employ a paid tax return preparer, little is known about the motivations for preparer use. Given the influence of preparers on a wide range of taxpayer decisions, including compliance, a better understanding of the determinants of preparer usage has relevance to both tax policy and administration.

Our empirical results are based on a balanced panel of tax returns for 1982–4, which spans the tax rate changes phased in by ERTA, in contrast to prior research that is primarily based on cross-sectional tax returns or surveys. We employ an estimation technique that controls for the unobserved individual-specific characteristics that are likely to affect preparation mode choice but that are constant over time. We find evidence of considerable heterogeneity across the taxpayers in the panel, which suggests that the panel data estimates are preferable to the cross-sectional estimates.

For the individual variables, our results provide several interesting findings. First, the time-cost of tax preparation is an important determinant of preparer usage, although its marginal effect is small. Time-cost is statistically significant even after controlling for complexity (modeled as the type of tax return filed and the number of additional forms and schedules attached to the return) and source of income. Second, we find that being self-employed significantly increases the probability of using a preparer, a result consistent with the consensus in the literature. Unlike previous studies, however, we find that preparer usage is negatively associated with the number of dependents and inferences about other demographic variables depend on itemization status. Finally, unlike previous cross-sectional studies, we do not detect an association between income or tax rate and preparer use after controlling for time-cost, complexity, and sources of income. Although panel data offer promise in providing evidence on the separate effect of income and tax rates, we are unable to examine this issue satisfactorily, because the correlation between these variables in our panel is simply too high.

We recognize several limitations in our data and empirical methods. Although the use of panel data brings some distinct advantages, it also has certain drawbacks, including the possibility of attrition bias. One characteristic of balanced panels of tax returns is that they underrepresent low income and elderly taxpayers and those filing as single (Christian and Frischmann, 1989).

Another limitation is the potential endogeneity of certain explanatory variables. Although we attempted to minimize this problem in the case of reported income and MTR by basing both on TPI, other predictors potentially are endogenous. For example, preparers might suggest the use of particular forms and schedules or recommend self-employment status, so inferences of directionality for these variables may be unwarranted. Finally, it is possible that the determinants of preparation mode may vary by preparer type (*e.g.*, CPA, attorney, enrolled agent, *etc.*). Previous studies have found that advice given by CPAs differs from that given by other types of preparers (Ayres, Jackson, and Hite, 1989). However, it is not possible to distinguish between preparer types in publicly available tax return data. To our knowledge, Dubin *et al.* (1992) performed the only econometric study that distinguishes between preparer types, but they use aggregated data from the Taxpayer Compliance Measurement Program.

For future work, we believe more recent data might provide new evidence on the motivations for preparer usage in light of tax reform and the changing environment faced by taxpayers. For example, the Tax Reform Act of 1986 fundamentally altered the tax system, reducing complexity for some and increasing it for others. Specifically, the proportion of taxpayers claiming itemized deductions dropped by 25 percent between 1985 and 1988. Recent rules relaxing eligibility for using Form 1040EZ and the availability of electronic filing and inexpensive software for tax return preparation may create different motivations for using paid preparers.

ENDNOTES

An earlier version of this paper was presented at the 1992 Annual Meeting of the American Accounting Association held in Washington, D.C. The paper has benefited from the comments of Seung Ahn, Bruce Behn, Pete Frischmann, Steve Kaplan, Phil Reckers, Hal Reneau, John Scholz, Joe Schultz, and, especially, Gary Weber. The valuable suggestions of the editor and three anonymous reviewers are also greatly appreciated. All remaining errors, of course, are ours.

[1] Besides compliance, return preparation mode is likely endogenous in models of other taxpayer behavior, such as decisions involving their prepayment position (refund/balance due), participation in savings incentives or amnesties, *etc.* Thus, modeling preparation mode choice is relevant to a broader group of studies.

[2] See also Chamberlain (1984) and Hsiao (1986) for general surveys of panel data techniques. For examples of the use of tax return panels in studying different taxpayer behaviors, see Slemrod and Shobe (1988); Auten, Burman, and Randolph (1989); Barrett (1991); and Christian and Gupta (1993).

[3] ERTA reduced the top marginal tax rate from 70 to 50 percent effective January 1, 1982. In addition to the reduction in the top rate, rates in general were reduced by 10, 10, and 5 percent, respectively, effective for the tax years 1982, 1983, and 1984.

[4] This differs from Long and Caudill (1987) who also require the payment of social security tax on self-employment earnings (*i.e.*, presence of Schedule SE) for the taxpayer to be considered self-employed. We do not follow their definition, because it excludes returns from the self-employed who report a loss.

[5] Reporting burden is the sum of estimated hours to learn about the law, prepare the return, and send the return. For "business" forms (as if self-prepared), the time required to obtain materials is also included along with the previous three. After-tax wage rate is measured as [(TPI * 10,000)/2,000] * (1 − MTR), which is the after-tax income scaled by the typical number of hours worked in a year.

[6] Although Long and Caudill (1987) also include the *state* MTR in two models, we do not for several reasons. First, as Long and Caudill (footnote 12) themselves acknowledge, obtaining a measure of state MTR is extremely complicated. Second, the state of residence of taxpayers with AGI exceeding $200,000 is not identified by SOI for confidentiality reasons; hence, these taxpayers have to be eliminated. Finally, after extensive analysis, Deere and Wolfe (1991) find that inferences about the effect of state MTR are similar to that of federal MTR in a preparer use model.

[7] Although a satisfactory measure of wage rate is unavailable in tax return data, it is necessary in estimating time-cost, because reporting burden by itself is difficult to differentiate from complexity. We tried several different proxies for wage rate, with little difference in the overall results. We are grateful to an anonymous reviewer for helpful comments on this issue.

[8] We limited our panel to 1982–4 to provide a contiguous period that spanned the tax rate changes of ERTA and that also allowed comparisons with Long and Caudill (1987).

[9] These returns are identified in the SOI Panel by the SSNCODE variable.

[10] A small number of returns in the SOI Panel are prepared by other than the taxpayer or a paid-preparer, such as returns prepared or reviewed by the IRS and returns prepared under the VITA, "self-help," or "tax counseling for the elderly" programs. These returns are excluded because they do not fall in either category. Neither Long and Caudill (1987) nor Deere and Wolfe (1991) mention excluding such returns from their sample. By implication, these returns are considered self-prepared in their study.

[11] See also Greene (1990) for a description and Cecchetti (1986) and Christian and Gupta (1993) for applications.

[12] The separate analysis was motivated by the fact that the after-tax cost of return preparation is relatively lower for itemizers, and there is empirical evidence that taxpayer compliance may depend on itemization status (Slemrod, 1989). To be included in this subsample, taxpayers were required to itemize in each of the three years in addition to meeting the sample selection criteria described before.

[13] Note that the LRs for the cross-sectional and panel data models in Table 2 are not comparable, because the latter is only a function of the slope parameters and not the fixed-effects themselves, which are never estimated (*i.e.*, there are no intercept terms in Panel B).

[14] The marginal effect for the kth explanatory variable is given by $[p(1-p)]\hat{\beta}_k$, where p is the proportion of paid-prepared returns in the sample. Thus, the marginal effect of 0.42 for EMP in Panel B of Table 2 is calculated as follows: $[0.4728(1 - 0.4728)] * 1.70$.

[15] While we find that Schedules E and G have similar marginal effects, Long and Caudill (1987) found Schedule E to have a marginal effect of 24 percent, nearly three times that of Schedule G.

[16] Specifically, 512 observations (7 percent) switch marital status and 211 (3 percent) switch between claiming and not claiming the age exemption during our three year panel.

[17] Long and Caudill's (1987, p. 37) explanation of this relationship appears to be the opposite of ours. They find a significant positive coefficient for the number of dependents and conclude that their result is consistent with the argument that paid-preparer usage by the nonelderly rises with age. Their conclusion is plausible, however, only if the number of dependents is expected to *increase* with the age of the nonelderly. Actually, this issue is complicated by the fact that in reality the relationship between number of dependents and age of the nonelderly is likely to be nonlinear. The number of dependents is likely to increase at first and then decline. Given the nature of tax return data, we do not observe age on a continuum. However, we expect that in panel data, one is more likely to observe taxpayers on the downward-sloping portion of the dependent-age curve.

[18] MTR rather than TPI was omitted for the reasons put forth in Feenberg (1987). Specifically, Feenberg argues that parameter estimates from incorrectly specified models containing MTR and its determinants (income, filing status, dependents, *etc.*) may reflect omitted interaction terms. However, he finds little difference between his instrumental variable estimates and those obtained with OLS in a model of charitable giving that contains more determinants of MTR than our model. We thank an anonymous reviewer for suggesting the additional analysis.

[19] Because using the IRS audit rate requires information on the state of residence of the taxpayer, these models were estimated only for taxpayers whose AGI did not exceed $200,000. As mentioned before, the state of residence of higher income taxpayers is not identified in the SOI Panel for confidentiality reasons.

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