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Further Evidence on Auditor Selection Bias and The Big 4 Premium

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FURTHER EVIDENCE ON AUDITOR SELECTION BIAS AND THE BIG 4 PREMIUM

Abstract

In recent years, the competitiveness of the corporate audit market has received a great deal of attention from policy makers and academic researchers alike. Among the main issues of concern is whether large auditors command a premium when setting fees for statutory audit services, and whether this is symptomatic of a lack of competition in the market for audit services or results from differences in the quality of the product offered by the big 4. A large number of academic studies based on independent data sets find a positive OLS coefficient on a large auditor binary variable in audit fee regressions and interpret this as evidence of a premium. However, recent research on UK private companies suggests that the large auditor premium is explained by auditor self-selection bias and that when this is controlled for using a two-stage Heckman procedure, the premium vanishes. In this paper we examine some of the difficulties in properly specifying the audit fee equation and discuss potential sensitivity of the estimates provided by the two-step model. We re-estimate audit fee equations for over 36,000 UK private companies employing a relatively new development in the applied econometrics literature – propensity score matching. In addition, we employ formal decomposition methods, which have not been used in the audit literature to date, to provide a more comprehensive analysis of big 4 premiums. Our results suggest that evidence of the large auditor premium vanishing when selection bias is controlled for do not seem to generalise and that the Heckman two-step procedure is highly sensitive to model specification. Matching results suggest that auditees of similar size, risk and complexity pay significantly higher fees to big 4 auditors.

Keywords: Audit fees; large auditor premium; propensity score matching; decomposition methods; selection bias

Data availability: Data are available from the sources described in the paper.

FURTHER EVIDENCE ON AUDITOR SELECTION BIAS AND THE BIG 4 PREMIUM

INTRODUCTION AND BACKGROUND

In recent years, the competitiveness of the market for audit services has been the subject of considerable attention from the accounting profession, regulators and academic researchers. Some of the main issues of concern are whether large auditors command a premium when setting fees for external corporate audit services and if so, whether such a premium is symptomatic of a lack of competition in the audit market or results from a higher quality product in competitive markets. In the UK, the Department for Trade and Industry and the Financial Reporting Council recently commissioned an extensive investigation of these issues (Oxera, 2006) and concluded that higher fees have resulted from higher concentration and that auditor reputation is important to companies, but that some large UK firms have no effective choice of auditor due to significant barriers to entry.

The empirical analysis in the Oxera report suggests that big 4 auditors are able to charge an average premium of around 18% for UK quoted companies. Furthermore, since the seminal contribution of Simunic (1980), there has not been universal agreement on this issue, but a large number of studies using independent data sets from a variety of markets and countries find a persistent positive OLS regression coefficient for top-tier (big 8, big 6 and big 4) auditors, for companies of various sizes, and interpret this as evidence of a premium (e.g., Pong and Whittington, 1994; Bandyopadhyay and Kao, 2004; Seetharaman et al., 2002; McMeeking et al., 2007; Ghosh and Lustgarten, 2006; Clatworthy and Peel, 2007). A survey of the international empirical evidence (Moizer, 1997, p. 61) reported that 'the results point to a top tier fee premium of between 16 to 37%'; while Hay et al. (2006, p. 176) note, in a meta-analysis of 147 published audit fee studies, that 'the results on audit quality strongly support the observation that the Big 8/6/5/4 is associated with higher fees.'

Notwithstanding the relatively persistent empirical finding of a large auditor premium in prior studies, recent research has investigated the important issue of the non-random selection of auditors by clients and its impact on observed large auditor premiums (Ireland and Lennox, 2002; Hamilton et al., 2005; and McMeeking et al., 2006). In a study of UK private companies, Chaney et al. (2004) fail to find a large auditor premium after they control for potential self-selection. Using OLS, they find a significant positive coefficient on a large auditor (big 5) binary variable, but when they employ a two-stage Heckman procedure to control for potential self-selection of auditors conditional on observable and unobservable client characteristics, the premium vanishes. Indeed, they conclude (p. 67) that 'if big 5 auditees had chosen non-big 5 auditors, their audit fees would have been higher.' Similar findings were reported by the same authors for a sample of US listed firms (Chaney et al., 2005). Given that previous studies report the absence of a premium after controlling for selection bias across different countries (the US and UK) and different audit markets (listed and private firms), their findings are of key import, since they imply that a large number of previous studies may have erroneously reported large auditor premiums.

The purpose of this paper is to present new evidence on the big 4 auditor premium and the effects of auditor selection for a large sample (36,674) of private UK firms. The audit market for private limited companies in the UK is more competitive than that for listed companies since the big 4 have a substantially lower market share and smaller auditors are less likely to be excluded (as in the listed market) from audits because of auditee size considerations. Hence any identified premium in this market is less likely to be related to oligopoly power, but rather to perceived auditor quality differences (such as those associated with auditor quality and reputation effects). Our cross-sectional sample is the largest yet employed in the UK private company audit market and the richness of our data set allows us to employ a variety of estimators to subject the issue of self-selection bias to considerable scrutiny.

We conduct a rigorous analysis of big 4 premiums using formal decomposition measures which have not previously been employed in the accounting and auditing literature. Previous analyses of the Heckman two-step findings suggest that they are highly sensitive to model specification, in contrast to OLS single-stage estimates (Hartman, 1991; Stolzenberg and Relles, 1997). We highlight a number of potential problems associated with the Heckman method, which may lead to doubts concerning the robustness of reported empirical findings on the large auditor premium. In particular, the econometrics literature emphasises the difficulties in properly 'identifying' the audit fee equation using the two-step Heckman model if the initial auditor selection equation shares common regressors with the audit fee equation and relies on the non-linearity assumption to identify the audit fee equation. This may lead to the Heckman method yielding results that are not robust and may result in severe collinearity problems (e.g., Little and Rubin, 1987; Puhani, 2000). Our analysis attempts to address these problems by examining the effect of sample selection, model specification and identification on the Heckman results.

A related approach adopted in the econometrics literature for overcoming self-selection bias involves matching procedures, particularly propensity score matching methods (e.g., Black and Smith, 2004; Simonsen and Skipper, 2006), which have yet to be employed in the auditing literature. Using these methods, we present new evidence on the large auditor premium using matched samples of companies audited by big 4 and non-big 4 auditors. Matching ensures that any observed premium is based on samples of comparable companies in that any big 4 auditee is matched with a non-big 4 auditee with similar observable characteristics.

Our results suggest that two-step corrections for selection bias in audit fee models are highly sensitive to model specification – a finding consistent with empirical results reported in applications of such models in other fields (e.g., Winship and Mare, 1992; Stolzenberg and Relles, 1997; Leung and Yu, 2007). Using more robust matching estimators, we conclude that the big 4 premium is still present after controlling for observable audit client characteristics and that models attributing the premium to unobservable characteristics should be treated with a degree of caution.

The remainder of the paper is organised as follows. In the next section, we outline general modelling issues and assumptions; section three describes our empirical models and data while our empirical results based on single stage, two-step and matching estimators follow in section four. The paper concludes in section five with a summary, implications and suggestions for future research.

MODELLING ISSUES AND THE BIG 4 PREMIUM

Evidence on the Premium in Prior Literature

To date, the auditing literature has advanced several (non-independent) reasons for large auditors charging higher fees, including the big 4 being associated with established reputations, higher quality audits, higher training costs, higher potential losses ('deeper pockets') and the occupation of a position of oligopoly in many audit markets (Moizer, 1997). Craswell et al. (1995, p. 298) note that in competitive markets, the large auditor premium relates to big 4 (formerly big 8, big 6) 'investments in brand name reputation for higher quality audits'. In the market for the largest (particularly international) companies, however, smaller auditors, due to their lack of technical resources and geographical coverage, are unable to compete; hence such auditees are limited in choice to big 4 auditors only. For example, the Oxera report (2006, p. i) concluded there were significant barriers to entry in the sub-market for large UK quoted companies, 'including the high cost of entry, a long payback period for any potential investment, and significant business risks when competing against the incumbents (big 4) in the market'.

Whether or not the auditee market is competitive (i.e., amongst the big 4) for the largest companies, or subject to cartel pricing behaviour, is clearly difficult to test, since no realistic counterfactuals exist. In the current study of UK private companies, the market is *a priori* competitive in that big 4 concentration is relatively low (8% of audits in our sample), with both big 4 and non-big4 auditors being represented across a wide size range of auditees. Hence, in such a market any observed premiums are more likely to be related to perceived and/or actual audit quality effects.[1]

We therefore assume a competitive market using the seminal audit fee framework of Simunic (1980) and developed by Pong and Whittington (1994). Simunic (1980) hypothesises that audit fee variations are associated with audit production functions, loss exposure and audit quality (modelled with reference to auditee size, complexity, risk and auditor [big 4] quality). Pong and Whittington (1994) posit

[1] For example, Blokdijk et al. 2006 find that the audit input mix differs between (then) big 5 and non big 5 auditors such that the quality of audits by the big 5 is actually higher, even though the total effort exerted is similar. Francis et al. (1999) report that Big 6 auditors constrain income-increasing discretionary accruals more than smaller auditors while Lennox (1999) finds that large auditors' reports are more accurate than smaller auditors.

that supply is related to auditors' cost functions, which is largely associated with the quantity of work/effort. Given the minimum audit standard is prescribed by statute and professional standards, Pong and Whittington (1994) state that the demand for audit is relatively inelastic. Furthermore, as noted by Simunic (1980, p. 170), in terms of product differentiation, the audit market is hedonic; i.e., differentiated audit products (quality) are not directly observed and 'the principal differentiation characteristic of the service is likely to be the identity of the supplier … it is the Big Eight firms which enjoy visibility and brand name recognition among buyers.'

The market for audit services among UK private companies is an interesting context in which to test for the presence of a large auditor premium. In addition to the more competitive nature of the supply side of the audit market, there are arguments both for and against the prediction that a big 4 premium will be observed. As argued by Chaney et al. (2004), lower agency costs for private firms (which are more closely held), potentially less reliance on financial statements by outsiders and lower litigation risk for auditors (compared to listed firms) would point to lower demand for high quality audit services, and thus to no expectation of a premium. By contrast, owners of private firms may wish to signal credibility of their financial statements should they wish to sell their stake and the absence of market values may make information provided by the financial reporting process *more* important (e.g. for managerial performance measures). In addition, there is evidence that newly public firms are able to attract cheaper debt capital if they appoint a large auditor (Pittman and Fortin, 2004), suggesting that more expensive audit fees may be recovered through the payment of lower rates of interest.

Statistical Specifications and Assumptions

Though we focus our discussion on the big 4 premium, our discussion is applicable to other areas of accounting and business research where selection bias is a potential problem. We divide companies into those companies with a big 4 auditor and those without. This division is indexed below by *BIG4* and *NON* and represented by a dummy variable (D) taking the value 1 if the auditee has a big 4 auditor and zero otherwise. The existing literature typically assumes that the natural log of audit fees (F) depends on

K variables (X_k k=1,..,K) capturing important client characteristics (principally measures of auditee size, complexity and risk) and employs a linear regression of the form:

$$\ln F_{BIG4}=a+b+\Sigma_k b_k X_{k\,BIG4} + e_{BIG4} \qquad \text{For big 4 clients } (D=1) \qquad 1.$$

$$\ln F_{NON}=a+\Sigma_k a_k X_{kNON} + e_{NON} \qquad \text{For non big 4 clients } (D=0) \qquad 2.$$

where the error term (e) reflects the unobservable random determinants of audit fees. Audit fees may vary between these groups because the observable characteristics (X) are different and/or because their impact on audit fees ($b\neq0$, $a_k\neq b_k$) are different. As noted by Pong and Whittington (1994) and Chaney et al. (2004), it is likely that big 4 auditors are better equipped to audit larger, more complex clients, though this may be offset in part by higher fixed costs from training audit staff.

Initially we assume (as in many previous studies) for our single stage conventional estimates that any unobservable auditee characteristics are the same for (D=1) and (D=0) so the errors have the same distribution for each type of auditor. A problem arises since we cannot directly compare the fees paid under each regime because we only observe a company as a client of either a big 4 or a non-big 4 auditor, but not both, i.e., we do not observe the counterfactual outcome.[2] But this problem can be overcome by assuming that the errors in each equation have the same distribution and that the values of the regressors are unimportant in respect of computing the counterfactuals; however, if there are large and significant differences in the values of the regressors for D=1 and D=0 then it is unreasonable to extrapolate between them.[3]

If the OLS estimates of the parameters are (a, a_k) for the non big 4 auditees and (a, b, b_k) for the big 4 auditees, then the predicted (log of) audit fees for a big 4 auditee, firm i, in each 'regime' are:

$\widehat{\ln F_{NONi}} = a + \sum_{k=1}^{K} a_k X_{ki}$ (the counterfactual value) and $\widehat{\ln F_{BIGi}} = a + b + \sum_{k=1}^{K} b_k X_{ki}$ (the actual value).

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[2] Another potential concern is the use of linear functions. It may be possible for the same non-linear audit fee equation to apply to both types of auditee so that any observed big 4 premium might be entirely 'explained' by auditees' different characteristics. A big 4 premium can still be predicted if linear approximations are estimated at markedly different points on the curve.

[3] For example, at the limit, it would be inappropriate to compare the audit fees paid by large and small companies if all large auditees employed big 4 auditors while all small ones employed non-big 4 auditors.

The big 4 premium is then the difference: $\widehat{\ln F_{BIGi}} - \widehat{\ln F_{NONi}} = b + \sum_{k=1}^{K}(b_k - a_k)X_{ki}$. Studies testing for a premium using a binary variable in a single regression assume that the slope coefficients for the big 4 and non-big 4 are identical (i.e., $\sum_{k=1}^{K}(b_k - a_k)X_{ki}$ =0) so the premium is *b*. In practice we compute these statistics for two 'typical' (average) auditees; the first has the values for the regressors equal to the mean values for the big 4 auditees ($\overline{X_{kBIG}}$) and the other the mean values for the non big 4 auditees ($\overline{X_{kNON}}$).[4] This gives two estimates (*P*) of the big 4 premium:

$$P_{BIG4} = b + \sum_{k=1}^{K}(b_k - a_k)\overline{X_{kBIG}} \qquad \text{and} \qquad P_{NON4} = b + \sum_{k=1}^{K}(b_k - a_k)\overline{X_{kNON}} \qquad 3.$$

P_{BIG4} is the predicted fees paid by a 'typical' big 4 auditee to a big 4 auditor minus the predicted fees paid by the same auditee to a non big 4 auditor. Although not used in previous auditing research, these statistics are widely used elsewhere as part of an Oaxaca-Blinder (OB) decomposition analysis (see e.g. Greene, 2003, p. 53 for further discussion). The OB decomposition writes the difference in the means of the log of audit fees as:

$$\overline{\ln F_{BIG4}} - \overline{\ln F_{NON}} = \sum_{k=1}^{K} a_k(\overline{X_{kBIG4}} - \overline{X_{kNON}}) + b + \sum_{k=1}^{K}(b_k - a_k)\overline{X_{kBIG4}} = EXPLAINED_{BIG4} + P_{BIG4} \qquad 4.$$

$$\overline{\ln F_{BIG4}} - \overline{\ln F_{NON}} = \sum_{k=1}^{K} b_k(\overline{X_{kBIG}} - \overline{X_{kNON}}) + b + \sum_{k=1}^{K}(b_k - a_k)\overline{X_{kNON}} = EXPLAINED_{NON} + P_{NON} \qquad 5.$$

This decomposition emphasises that the observed actual difference in audit fees can partly be attributed to the different characteristics of the big 4 and non big 4 auditees and partly by the big 4 premium. Recent developments in the auditing literature, however, point out that OLS estimates of the big 4 premium are potentially biased because auditors are not appointed randomly and because auditor choice is systematically related to auditees' unobservable characteristics, such as the quality of internal controls and insider knowledge of the riskiness of future cash flows. As noted by Ireland and Lennox (2001, p. 75), 'although the standard OLS audit fee models control for observable differences, characteristics that are not observable to the academic researcher may affect both fees and auditor choice and thereby cause bias.' In

[4] This choice ensures that the errors play no role as the means of the predicted errors are zero.

this context, Titman and Trueman (1986) and Datar et al. (1991) each develop models predicting that auditor quality is a function of firm-specific risk, of which firm insiders are better informed than outsiders. However, both models make competing predictions about the nature of the relationship between firm-specific risk and auditor quality. In particular, Datar et al. (1991) predict that entrepreneurs of risky firms choose higher quality auditors, whereas Titman and Trueman (1986) predict the opposite.

Selection bias arises if the unobservable characteristics of big 4 and non-big 4 auditees are systematically different from each other. Suppose for example e_{NON} and e_{BIG4} are drawn from the same distribution but that the big 4 auditees only have positive errors while the non-big 4 auditees only have negative ones.[5] Then $E(e_{BIG4})>0>E(e_{NON})$. This effect can be modelled by writing the errors as $e_{BIG4}=E(e_{BIG4})+e$ and $e_{NON}=E(e_{NON})+e$ where e is pure random error uncorrelated with auditor choice and the regressors. Estimating audit fee equations with standard single-stage OLS omits the conditional means (by assuming $E(e_{BIG4})=E(e_{NON})=0$) and leads to inconsistent estimates if these terms are correlated with the regressors. In contrast the Heckman two-step procedure provides an estimate of the mean of the conditional error known as the Inverse Mills Ratio (IMR) or the selection term l that can be added to the regressors. The selection term is estimated by modelling the auditor choice process via a simple probit selection model (step one), where each company has an unobserved propensity (D^*) to choose a big 4 auditor. D^* is a linear function of M regressors (Z_m m=1,.., M) and other unobservable characteristics (e_{SEL}). The model is thus:

$$D^*=d+\Sigma_m d_m Z_m+e_{SEL} \qquad \text{Auditor choice equation} \qquad 6.$$

$$\ln F_{BIG4}=a+b+\Sigma_k b_k X_{kBIG4} + e_{BIG4} \qquad \text{For big 4 auditees} \qquad 7.$$

$$\ln F_{NON}=a+\Sigma_k a_k X_{kNON} + e_{NON} \qquad \text{For non big 4 auditees} \qquad 8.$$

If $D^*>0$, D=1 and we observe $\ln F= \ln F_{BIG4}$. Otherwise $D^*\leq 0$, D=0 and $\ln F= \ln F_{NON}$. The model is completed by assuming that the errors of the selection equation and fee equations are jointly normal with

[5] For example, if the positive error measures the unobserved value to the auditee of appointing a big 4 auditor, then big 4 auditees will value big 4 auditors more than non big 4 ones and therefore pay higher audit fees.

zero means, constant variances and covariances: E($e_{SEL}e_{NON}$)=s_{SNON} and E($e_{SEL}e_{BIG4}$)=s_{SBIG4}. It is the implied correlation between the unobservable factors determining respectively the choice of auditor type and audit fees[6] that enables the estimation of this model.

The Heckman two-step method for this model is based on the following equations:

$$\ln F_{BIG4}=a+b+\Sigma_k b_k X_{kBIG4} + s_{SBIG4}\, l_{BIG4} + u \qquad \text{For big 4 auditees} \qquad 9.$$

$$\ln F_{NON}=a+\Sigma_k a_k X_{kNONk} - s_{SNON}\, l_{NON} + u \qquad \text{For non-big 4 auditees} \qquad 10.$$

where
$$l_{BIG4} = \frac{f(\Sigma_m d_m Z_m)}{\Phi(\Sigma_m d_m Z_m)} \quad \text{and} \quad l_{NON} = \frac{f(-\Sigma_m d_m Z_m)}{\Phi(-\Sigma_m d_m Z_m)} \qquad 11.$$

and where f is the normal density function and Φ the normal distribution function. The probit auditor choice model yields estimates of the selection terms l_{BIG4} and l_{NON} which are included in the audit fee equations in the second step. OLS applied to the augmented equations (i.e. including l_{BIG4} and l_{NON}) yields consistent coefficient estimates and standard hypothesis tests can be applied with modified formulae for the standard errors.[7] The selection and audit fees equations in the Heckman model can also be estimated by maximum likelihood (ML), which leads to more efficient estimates if the model is correctly specified. ML estimates do, however, require the maximisation of a complex likelihood that may be more sensitive to model mis-specification than conventional estimates. Accordingly, we report both conventional Heckman estimates and maximum likelihood estimates (MLE) for our two step models.

Although the Heckman procedure has become increasingly popular in auditing research, (and indeed in other areas of accounting and finance – see, for example, Li and Prabhala, 2007), its robustness has been questioned under certain conditions. For example, Giles (2003, p. 1299) notes 'Heckman's

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[6] For instance, companies more likely to employ big 4 auditors (i.e. have 'large' e_{SEL}) given their observable characteristics (Z) are likely to value unobservable aspects of big 4 auditors' services more highly (i.e. have 'large' e_{BIG4}).

[7] The fees equation for non big 4 auditees is estimated with selection into non Big 4 (i.e. the dependent variable for the probit is ND=1 if the firm is a non big 4 auditee). The coefficient of the selection term in this estimation is the covariance between the error in the selection equation determining whether ND=1 and e_{NON} i.e. an estimate of $-s_{SNON}$. All the results below for the non big 4 fees equation report estimates of s_{SNON}.

sample selectivity correction methodology offers a way of improving on the estimates obtained with non-random samples. While there is improvement in general in this regard, there are situations in which the correction for sample selectivity actually aggravates the problem.' Potential collinearity between the selection term and the other regressors in the second stage equation can cause severe problems. In addition some researchers identify the second stage equation via the non-linearity of the selection term only. However, recent econometric (particularly Monte Carlo) studies suggest that to adequately identify the model it should contain an instrument – that is a regressor which determines the choice of auditor but has no significant effect on determining audit fees (Little, 1985; Puhani, 2000). But collinearity may still cause problems when an instrument (also known as an exclusion or identifying variable) is employed, leading to unstable estimates (Stolzenberg and Relles, 1997; Leung and Yu, 2000; Li and Prabhala, 2005). Against this background, it is perhaps unsurprising that empirical results in auditing studies using the Heckman model have, to date, been mixed. Ireland and Lennox (2002) and McMeeking et al. (2006) report that the large-auditor premium is higher when self selection is controlled for, whereas Chaney et al. (2004; 2005) find the opposite: i.e., firms that chose (then) big 5 auditors would have been charged more had they selected a non-big 5 auditor.

In the absence of satisfactory instruments, the selection effect is only identified by extreme observations of the selection term l for example, those companies whose probability of choosing a big 4 auditor is estimated to be close to 1 in the probit model.[8] These big 4 auditees (usually because of their large size and complexity) effectively have no surrogate non-big 4 counterfactuals – that is, there is no 'common support' - the common support region being where big 4 clients have non-big 4 counterparts with similar characteristics. Following Black and Smith (2004), we therefore test in this paper the robustness of the Heckman results by re-estimating our models without the extreme observations of the selection term.

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[8] It should be noted that generally, the selection term is highly non-linear for large values of the standard normal variate.

This problem of producing adequate counterfactuals motivates matching methods as an alternative to the Heckman approach. Such methods are gaining in popularity in the social science literature (e.g. Bryson, 2002; Malo and Muna-Bullon, 2005; Diaz and Sudhanshu, 2006) and are based on matching the observable characteristics of members in the treatment group (i.e., big 4 auditees in our case) to members (counterfactuals) in the untreated group (non-big 4 auditees). Matching circumvents the requirement of linear functional form assumptions, the common support issue and exclusion restrictions (Bryson, 2002; Black and Smith, 2004) discussed above. However, there are various matching estimators to choose from. In particular, there is an essential trade-off in respect of how closely variables are matched (especially continuous variables), together with the number of variables used for matching, and the sample size – often referred to as the 'curse of dimensionality' (Ho et al., 2007) – such that matching closely on more than a few variables can result in prohibitively small matched samples unsuitable for any meaningful analysis.

The important assumptions made with matching concern the issues of common support and conditional independence.[9] The former assumption emphasises the need to compare like with like: if the big 4 premium is regarded as applicable to any auditee, then clients should be able to change their auditor and pay the corresponding counterfactual fees. The focus of attention is thus on similar big 4 and non-big 4 auditees and hence companies are excluded from the analysis where, based on their observable characteristics, they are very highly likely to employ either big 4 or non-big 4 auditors.

The conditional independence assumption requires that the value of audit fees is independent of auditor type given the values of some observable variables ($\boldsymbol{Z}\equiv\{Z_1,..,Z_M\}$). More formally:

$$\ln F_{BIG4}, \ln F_{NON} \perp D | \boldsymbol{Z} \qquad 12.$$

It is thus assumed that any systematic effect of the choice of auditor (D) on audit fees can be completely explained in terms of some observable variables ($\boldsymbol{Z}$). In practice, $\boldsymbol{Z}$ is interpreted as the

[9] A third assumption – stable unit treatment value assumption (SUTVA) – is also made. The SUTVA means that the use of big 4 auditors should not indirectly affect the non big 4 auditees.

determinants of the auditor choice decision. An implicit assumption is that the choice of auditor type does not affect the value of any $\boldsymbol{Z}$ thus affecting the choice of which variables to include in $\boldsymbol{Z}$.

The matching method technique used in the current paper and which has recently been applied in the applied econometrics literature (see e.g. Black and Smith, 2004; Simonsen and Skipper, 2006), but not to our knowledge in auditing research to date, is propensity score matching. This method relies on matching big 4 and non-big 4 auditees on the basis of the predicted probabilities (propensity scores) derived from a probit auditor choice model (in our case the first stage probit auditor selection model from the Heckman procedure). Consider the following semi-parametric matching model (with the selection equation repeated for later reference):

$D^{*}=d+\Sigma_m d_m Z_m+e_{SEL}$	Selection equation	13.
$\ln F_{BIG4}=m_{BIG4}(\boldsymbol{Z})+e_{BIG4}$	For big 4 auditees	14.
$\ln F_{NON}=m_{NON}(\boldsymbol{Z})+e_{NON}$	For non big 4 auditees	15.

If $D^{*}>0$, $D=1$ and we observe $\ln F=\ln F_{BIG4}$. Otherwise $D^{*}\leq 0$, $D=0$ and $\ln F=\ln F_{NON}$. The audit fee equations have additive errors but may be nonlinear in the conditional mean values (m_{BIG4} and m_{NON}). These means may depend on other regressors but the conditional mean independence assumption (*CIA*) means that the only relevant determinants are contained in ($\boldsymbol{Z}$).

To illustrate the matching approach, consider each big 4 auditee in turn and, where possible, identifying non big 4 auditees with characteristics similar enough to those of the big 4 auditees to be regarded as the same. This can usually only be achieved when the original explanatory variables are employed for a small subset of big 4 auditees, because some big 4 clients lie outside the common support region, that is, there is no non-big 4 auditee sufficiently close to make an effective match. Let M be the set of N_M matched pairs of firms. The estimated treatment effect for each matched big 4 auditee is defined as:

$$D(\boldsymbol{Z}_i)=\ln F_{BIG4}(\boldsymbol{Z}_i)-\ln F_{NON}(\boldsymbol{Z}_i) \quad i\in M \qquad 16.$$

The estimated big 4 premium (D), or the treatment effect, is the sample mean of these differences across all values of $\boldsymbol{Z}$ in M or the difference in the sample means. Hence:

$$\Delta = \left[\frac{1}{N_M} \sum_{i \in M} \ln F_{BIG4}(\boldsymbol{Z}_i) \right] - \left[\frac{1}{N_M} \sum_{i \in M} \ln F_{NON}(\boldsymbol{Z}_i) \right] \qquad 17.$$

$$\Delta = \overline{\ln F_{BIG4M}} - \overline{\ln F_{NONM}} \qquad 18.$$

where the subscript M indicates that the mean is for companies in the matched sample.

An important advantage of the propensity score approach is that matching is conducted with reference to only one variable (the propensity score, which varies between zero and one) rather than on a large number of individual (often continuous) explanatory variables, which is typically impractical. The propensity score is:

$$p(\boldsymbol{Z}) \equiv \Pr(D=1|\boldsymbol{Z}) \qquad 19.$$

We estimate the selection equation using a parametric estimator (in our case a probit model) and find the predicted probabilities (propensity scores) of choosing a big 4 auditor for all the firms in our samples. We then closely match each big 4 auditee to a non big 4 auditee that has a very similar propensity score. The estimated premium for each matched big 4 auditee is defined as:

$$D(\mathbf{Z}_i) = \ln F_{BIG4}(p(\mathbf{Z}_i)) - \ln F_{NON}(p(\mathbf{Z}_i)) \qquad i \in M \qquad 20.$$

where M is the set of N_M matched pairs of firms. The estimated big 4 premium (D) is the sample mean of these differences across all values of $p(\mathbf{Z})$ in M, or the difference in the sample means:

$$\Delta = \left[\frac{1}{N_M} \sum_{i \in M} \ln F_{BIG4}(p(\boldsymbol{Z}_i)) \right] - \left[\frac{1}{N_M} \sum_{i \in M} \ln F_{NON}(p(\boldsymbol{Z}_i)) \right] \qquad 21.$$

As noted by Black and Smith (2004, p. 110), the logic underpinning this method is ‘that subgroups with values of X [explanatory variables] that imply the same probability of treatment can be combined because they will always appear in the treatment and (matched) comparison groups in the same proportion. As a result, any differences between subgroups with different X but the same propensity score balance out when constructing the estimates.' An important limitation of matching approaches, however, is that they are, by their very nature unable to formally control for any unobserved auditee characteristics which may influence the variable of interest (audit fees). Thus, as noted by Dehejia and Wahba (2002, p. 153): 'Intuitively, this assumes that, conditioning on observable covariates, we can take assignment to treatment to have been random and that, in particular, unobservables play no role in the treatment assignment; comparing two individuals with the same observable characteristics, one of whom was treated and one of whom was not is … like comparing those two individuals in a randomized experiment'. While the Heckman approach solves this problem by allowing unobservable factors to influence auditor choice, there is a trade-off in practice due to the sensitivity to specification discussed above.

The second matching approach we take is an intermediate one which combines matching with the standard OLS regression used in the majority of prior studies. Following previous research that highlights the potential pitfalls of model sensitivity (Ho et al., 2007), initially we preprocess our data and then estimate the standard audit-fee model with a binary big-4 indicator variable. Preprocessing involves matching big 4 and non-big 4 auditees only on key attributes (in the current study, being well-tested measures of auditee size, complexity and risk) thereby ensuring sufficient matched observations to conduct standard (in the current case OLS regression) techniques to control for any remaining confounding factors. As stated by Ho et al. (2007, p. 3) this approach combines the merits of both non-parametric matching with conventional parametric estimators: 'In a sense our recommendations already constitute best practice since matching alone is not a method of estimation and always requires some technique to compute estimates … we simply point out that, except in the extraordinary case where matching is exact, parametric procedures have the potential to greatly improve causal inferences even after matching.'

Given the importance of the large auditor premium to academic researchers and policy makers, we test for its presence using all the methods outlined above. Firstly we employ the two-stage Heckman estimator (including an exclusion variable) and, following Black and Smith (2004), we test for the robustness of the results by re-estimating them in respect of the common support region. We follow this with both propensity score matching using predicted probabilities derived from the parameters of our auditor selection model and the semi-parametric matching procedures advanced by Ho et al. (2007).

EMPIRICAL MODELS AND DATA

Variables

The variables used in our audit fee model (see Table 1) have been widely employed in prior research (e.g., Simunic, 1980; Pong and Whittington, 1994; Chan et al., 1994; Ezzamel et al. 1996; Chaney et al., 2004; McMeeking et al., 2006; Clatworthy and Peel, 2007).

Insert Table 1 about here

Since corporate size (serving as a proxy for audit effort) has been found to be the key driver of external audit fees in previous research, we employ both total assets and turnover as size measures in our research. Pong and Whittington (1994, p. 1075) note that audits have two broad dimensions: ‘an audit of transactions and verification of assets. The former will be related to turnover and the latter to total assets.’ Following the vast majority of previous studies, we specify the relationship between audit fees (lnAFEE) and the size measures for turnover (lnSAL) and total assets (lnTA) in natural logarithmic form to capture potential economies of scale in the audit. In order to control for audit complexity, we include a variable labelled SQSUBS, defined as the square root of the number of subsidiaries (e.g., Francis and Simon, 1987), and EXPSAL - the ratio of non-UK turnover to total turnover (e.g., Beatty, 1993; Chaney et al., 2004), both of which we expect to be positively related to audit fees.

To capture auditee risk characteristics, we employ the ratio of total liabilities to total assets (TLTA) and the ratio of net profit before tax to total assets (RTA), which we expect to be positively and negatively related to audit fees, respectively (e.g., Chan et al., 1993 and Firth, 1997). Following previous research (e.g. Palmrose, 1986; Chaney et al., 2004; Clatworthy and Peel, 2007) we employ three additional binary variables to capture incremental risk/complexity in the audit. These are whether (coded

1) or not (coded 0) the audit client received a qualified audit report (QUALIF), reported exceptional and/or extraordinary items (EXITEM), disclosed a post-balance sheet event (PBAL) or a contingent liability (CONLIAB). All these variables are expected to be positively related to audit fees (ibid.).[10]

Finally, we include binary variables for whether (coded 1) or not (coded 0) companies are audited by a big 4 auditor (BIG4), whether the audit client's year end falls in December or March (BUSY) and whether the company is located in London (LOND). The latter two variables are expected to be positively related to audit fees in that companies audited during the 'busy' period may be charged higher fees and companies located in London are expected to pay higher audit fees reflecting cost of living differentials (Chaney et al., 2004; Clatworthy and Peel, 2007).

Other than in respect of corporate size and complexity, the literature motivating the choice of variables in the auditor selection model is less developed and is usually based on including a sub-group of variables from the audit fee equation in the selection model (Chaney et al., 2004; 2005; Hamilton et al., 2005, though cf. Ireland and Lennox, 2002) and/or relying on identifying the selection model via non-linearity only. As discussed above, these approaches are problematic, since neither a subset of the regressors from the fees equation nor the non-linearity may be adequate to identify the effects of selectivity bias.

If one assumes that firms choose auditor type by comparing their predicted costs (fees), the choice of auditor type depends on all the factors affecting the fees charged by either type of auditor. Thus all regressors in the fees equations enter the auditor choice model. While it is important to include an identification variable that is significantly associated with auditor choice (in the probit model), but not with audit fees (in the fees equation), such identification variables are extremely hard to obtain in practice (see e.g. Puhani, 2000). The present study is no exception. We attempted several plausible instruments[11]

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[10] Because company records on FAME only indicate whether or not either of these events occurred, we are unable to refine PBAL or CONLIAB to take account of the types of events or the nature of liabilities. Hence, we assess the average impact of these events. We also note that we are unable to ascertain the nature of the qualification from FAME and hence through QUALIF, we again measure the average impact of a qualified audit report.

[11] These included changes in sales, change in equity, change in total assets and various transformations.

and found only one – the change in the absolute value of total assets (CHTA) between the current and preceding year – which was statistically significant (and with the expected sign) in the probit selection model, but statistically insignificant when included in the OLS audit fee models.[12] Furthermore it is not formally a 'weak' instrument since it has an *F*-statistic of 11.21 for the null that it is insignificant in the regression of auditor type (*D*) on all the regressors. This exceeds the critical value of 8.96 for the validity a single instrument given by Stock et al. (2002) and the informal value of 10 that is widely used and advocated by Stock and Watson (2003 p.350).

Our motivation for including CHTA in the selection model is that companies which are involved in relatively large investments/acquisition or divestments/sale of assets, may require the expertise of a big 4 auditor due to the additional complexity of the audit. In addition, Keasey and Watson (1994) note that the absolute change in firm size (total assets) may from an agency perspective, act as a proxy for contractual changes at the firm level, which could give rise to a change in the demand for auditing services. Hence, large auditors may be associated with reducing agency costs (e.g., Ireland and Lennox, 2002), in companies with large asset variations. Although it has desirable theoretical qualities, it is also employed for pragmatic reasons, since it fulfils its main purpose of properly identifying the audit fee equations.

Following previous studies (e.g., Chaney et al., 2004; Hamilton et al.,, 2005), we expect the variables reflecting auditee size and complexity to be positively associated with the choice of a big 4 auditor in the probit model, in consequence of their hypothesised capacity to provide more efficient audits and to reduce agency costs (ibid.). In line with prior research (e.g. Ireland and Lennox, 2002; Chaney et al., 2004; 2005), we also expect our auditee risk variables to be positively associated with the selection of a big 4 auditor. As noted by Hamilton et al. (2005, p. 9), 'The greater the client's risk, the higher the propensity for the impairment of agency relationships. To mitigate the associated agency costs, higher quality auditors, surrogated by big 4, are more likely to be selected to signal the credibility of reporting.'

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[12] The t-values on CHTA when included in models 1, 2 and 3 were, respectively: 0.05, 1.32 and 0.18.

Furthermore, Datar et al. (1991) predict, and Copley and Douthett (2002) find, a positive relationship between auditee risk and the appointment of a higher quality auditor.

With regard to the final two variables (LOND and BUSY), we have no strong priors on their influence on auditor choice, other than that the univariate results of extant studies (as in the current study) have consistently reported (for both private and quoted audit clients) that a significantly higher proportion of big 4 auditors conduct their audits during the busy period – but that a significantly higher proportion of non-big 4 auditors are appointed to companies located in London (e.g., Ireland and Lennox, 2002; Chaney et al., 2004).

Data

The source of our data in the Bureau Van Dijk FAME DVD-ROM UK database. Financial (annual accounts data) and non-financial data (e.g., company location, auditor and audit qualification) are available as individual records for each company on the database. Companies were selected for inclusion in the study if they met the following criteria: their primary activities (according to FAME primary Standard Industrial Classification codes) were outside the financial sector; they were private limited companies; they were 'live' companies (i.e. had not ceased trading, failed or entered into voluntary liquidation); their audited accounts were available on FAME; they had full data available, including total assets and sales (minimum £1000), audit fee (minimum £100), and a disclosed profit/loss figure. In order to avoid the potential confounding influences of including both holding companies and their subsidiaries in the regression model (e.g., Ezzamel et al., 1996; Peel and Roberts, 2003), our sample only includes independent companies (i.e., those not held as a subsidiary of another company). In line with previous studies (e.g., Firth, 1997), financial companies were excluded due to the different composition of their financial statements and only live companies were selected to avoid the confounding influence of including non-live auditees. In addition, and in line with previous research, 11 companies with joint auditors (none of which were big 4 auditors) were excluded from the analysis to comply with the binary nature of the probit model. Following these restrictions, we obtained financial and numerical data, together with non-financial data, for 36,674 private companies from FAME for the latest financial statements available (predominantly for the calendar year 2003).

It is important to note (for it has implications for the sample size and for data accuracy) that the FAME default setting for downloading data is £000s, with data being rounded to the nearest £1000; for example an audit fee of £1550 would be rounded to £2000 and one of £400 to zero (i.e. a missing value.) Data can, however, be downloaded (as in the current study) in £ and hence neither data accuracy nor observations are lost using this option.[13]

Insert Table 2 about here

Descriptive statistics for the variables used in our analysis are presented in Table 2. The average audit fee (AFEE) for the whole sample (*n* = 36,674) amounted to £7.80k, with companies having mean sales (SAL) and total assets (TA) of £7.97m and £5.86m respectively – and with companies ranging from a minimum of £1k to a maximum of £4,979m for sales and £1k to £5,234m for total assets. Table 2 also shows that, other than in respect of audit qualifications (QUALIF), all the variables differ significantly (in respect of means, medians and proportions) between the big 4 (*n* = 3,038) and the non-big 4 (*n* = 33,636) sub samples. In particular, and consistent with prior expectations, we note that big 4 clients are significantly larger (as measured by both SAL and TA), have more subsidiaries (SUBS), a higher proportion of foreign to total sales (EXPSAL) and are more likely to report post balance sheet events (PBAL), contingent liabilities (CONLIAB) and exceptional items (EXITEM). In addition, on average, big 4 clients exhibit lower profitability (RTA) but higher gearing (TLTA), are less likely to be located in London (LOND), but more likely to be audited during the busy period (BUSY), and are associated with a significantly higher absolute change in the value of total assets (CHTA).

Because of the large number of small auditees represented in the non-big 4 sample, the mean and median values of the size variables for big 4 auditors are substantially larger (mean sales and total assets

[13] The sampling consequences of this are not trivial since it captures a large number of smaller firms. For instance, Chaney et al. (2004), who download data in £000 and deleted many small companies due to imprecision, report big 4 concentration of 50% compared to 8% in our sample; furthermore, the mean total assets for companies in their sample is £24.28 million whereas the corresponding figure in our study is £5.86 million.

of £39.41m and £35.62m) than for the non-big 4 auditors (mean sales and total assets of £5.13m and £3.17m).

EMPIRICAL RESULTS

We commence our analysis with standard single-stage OLS regression under the assumption of no selection bias. We then report our comparative analysis employing the two-step Heckman procedure, together with associated robustness tests. Finally, we present the results of the matching procedures.

Single stage results

Model 1 in Table 3 shows that the OLS estimates for the standard pooled audit fee specification, which is employed in the vast majority of previous studies. All explanatory variables exhibit their expected signs and, other than the busy period variable (BUSY), which is statistically significant at the 0.10 level (p=0.079) all are highly significant (p<0.0001 in all cases). In particular, we note that the BIG4 coefficient (0.270) implies[14] that, on average, the audit fees of a non-big 4 auditee would increase by 31% if it were to employ a big 4 auditor. Also noteworthy is that the model explains a relatively high proportion (R^2 of 78%) of the variation in the audit fees of UK private companies, comparing favourably with that (57%) reported by Chaney et al., (2004) for their sample of UK private firms.

Models 2 and 3 in Table 3 report OLS estimates for audit fee equations for the big 4 and non-big 4 auditee samples respectively. Model 1 assumes the same specification for big 4 and non-big 4 auditees. However, in common with Chaney et al. (2004) a joint *F*-test rejected the null hypothesis (F = 13.43; p=0.000) that the coefficients in the two models (2 and 3) were the same, implying that the fee setting process differs between the two auditor types. The focus of our empirical analysis is therefore models 2 and 3 in Table 3 (i.e., those which allow the slope coefficients of the explanatory variables to differ for big 4 and non-big 4 auditees).

Insert Table 3 about here

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[14] We use the standard transformation $e^x - 1$ (where x = the coefficient/mean log difference) to compute percentages reported in the paper.

Table 3 shows that for the non-big 4 specification (model 3) all the explanatory variables exhibit their expected signs and, other than for BUSY which loses statistical significance (p = 0.131), all variables are highly significant (p < 0.0001 in all cases). For the big 4 specification (model 3) in addition to BUSY, the coefficient sign on the gearing variable (TLTA) is negative, but statistically insignificant – a finding in common with Chaney et al. (2004) for their big 4 equation; furthermore, the intercept in model 2 is larger than that in model 3 – a result also found by Chaney et al. (2004), which they attribute to big 4 auditors recovering their higher expenditure on training and facilities.

To examine the premium in more detail, we use the OB decomposition (discussed above) on our estimates for models 2 and 3. Firstly, the OB decomposition based on measuring the premium using the characteristics of the big 4 auditees is:

$$\overline{\ln F_{BIG4}} - \overline{\ln F_{NON}} = \sum_{k=1}^{K} a_k(\overline{X_{BIG4k}} - \overline{X_{NONk}}) + b + \sum_{k=1}^{K}(b_k - a_k)\overline{X_{BIG4k}} \qquad 22.$$

Actual difference = Explained by characteristics + big 4 premium

9.4364-7.9099	=	9.1809-7.9099	+	9.4364-9.1809	23.
1.5265	=	1.2709 (263.6)	+	0.2556 (21.87)	

Greene (2003, p.54) provides the formulae for the estimated standard errors of each term in the decomposition and we report the *t*-values in parentheses. There is a large and significant (p = 0.000) difference in the means of the audit fees paid by companies audited by big 4 and non big 4 auditors (1.5265) using parameters from models 2 and 3. Most of this is accounted for by differences in their respective client characteristics (1.2709 or 83%). Nonetheless there is, on average, a significant (*p* = 0.000) big 4 premium of 0.2556, indicating a big 4 mark-up of 29.1%, which is close to that (31.0%) estimated in the pooled OLS equation (Model 1). On average, big 4 auditees paid audit fees of £12,537

($e^{9.4364}$), but would have paid £9,710 if they were charged according to the non-big 4 parameters (model 3) - a reduction of 23%.[15]

Hence, the results, based on conventional single-stage OLS estimates, reported in Models 2 and 3 are consistent with the presence of a big 4 audit premium (at least in the absence of potential selectivity bias). The next section presents our two-stage results where we analyse the extent to which the findings in this section are affected by selection bias.

Heckman Two-Step Regressions

Table 3 shows the two-step results with maximum likelihood estimates (MLE) and standard Heckman two-step estimates. Model 4a (4b) reports the probit selection model estimates for the choice of a big 4 auditor while models 5a (5b) and 6a (6b) report the MLE (standard Heckman) audit fee regression estimates for the big 4 and non big 4 auditees, including the additional parameter l (for the IMR estimated from the coefficients in model 4) to control for selection bias.

The probit selection models 4a and 4b show that other than for the variables CONLIAB and lnSAL, all the explanatory variables and significantly associated with auditor choice. In particular, the coefficient on the identifying variable (CHTA) exhibits its expected sign and is highly statistically significant ($p = 0.000$).[16] Also consistent with prior expectations and previous research, Model 4 shows that larger (lnTA) more complex (SQSUBS; EXPSAL) and higher risk (RTA; TLTA) companies are more likely to appoint a big 4 auditor. Companies receiving audit qualifications (QUALIF) are more likely to employ a non-big 4 auditor in contrast to those reporting a post-balance sheet event (PBAL) and auditees based in London, which are less likely to select a big 4 auditor, but are more likely to do so if their account year ends fall in the busy period (BUSY). The Wald chi-squared statistic of 2668.40 ($p < 0.0001$)

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[15] The results for non-big 4 clients also implied a statistically significant premium (at $p = 0.000$) of 31%.

[16] The statistical insignificance of lnSAL in the auditor choice equation is not related to collinearity with CHTA. When CHTA was removed from Model 4, lnSAL remained statistically insignificant. In addition, when lnSAL was removed from Model 4, CHTA remained positive and statistically significant.

for Model 4b indicates the selection equation is well determined; the McFadden's R^2 is 0.204 the model correctly classifies (using a cut-off point of 0.083)[17] 77.52% and 70.81% of the big 4 and non-big 4 auditees respectively, with an overall correct classification rate of 71.37%.

The audit fee equations exhibit the same pattern of significance levels as the single stage estimates in Models 2 and 3. Informally the estimates appear to be similar in magnitude except for the constant in the big 4 equation, which has a smaller value for the MLE in Model 5a (1.967 compared with 2.638). Of more import is the positive l coefficient, which is statistically significant at the 5% level in the non-big 4 (p = 0.000) model and in the big 4 model (p = 0.036), implying significant evidence of selection bias. The positive MLE estimate of 0.142 (Model 5a) for the covariance s_{SBIG} and the negative one of -0.199 (Model 6a) for s_{SNON} imply that an increase in the value for the unobservable error in the auditor selection equation ($\boldsymbol{e}_{SEL}$) is associated with an increase in the value of unobservable component of big 4 fees ($\boldsymbol{e}_{BIG4}$) and a decrease in the value of unobservable component of non big 4 fees ($\boldsymbol{e}_{NON}$), though the former estimate is insignificant at the 0.05 level.

To illustrate this, consider two firms with identical observable characteristics ($\boldsymbol{Z}$) which choose different types of auditor. The big 4 auditee has a larger unobservable error in the auditor selection equation (i.e., $\boldsymbol{e}_{SEL}$ is smaller). In this sense, big 4 auditors will have larger values of $\boldsymbol{e}_{SEL}$ but the estimated covariances indicate that larger values of these errors are associated with larger values of $\boldsymbol{e}_{BIG}$ and smaller values of $\boldsymbol{e}_{NON}$. These estimates imply that big 4 auditees will tend to pay *higher* fees in the big 4 fees equation and *lower* fees in the non-big 4 equations because of their unobserved characteristics. The converse also applies: non big 4 auditees will tend to pay *lower* fees according to the big 4 fees equation

[17] Note that this cut-off point (0.083) is the mean value of both the binary dependent variable and the predicted probabilities derived from the probit model. It reflects the prior probability (that is with a constant only probit model) of the selection of a big 4 auditor. It is an equivalent cut-off point (0.5) to that used in many studies where equal (or approximately equal) sub-samples are employed in logit/probit models. Note also that the McFaddens R^2 gives cognisance to the foregoing in that it is calculated as: unity minus log likelihood at convergence (full probit model) divided by log likelihood at zero (constant only probit model).

and *higher* fees according to the non big 4 equation because of their unobserved characteristics. Thus the effect of the unobservables is to cause private companies to choose the most expensive auditor.

These results are not consistent with cost minimisation and directly contradict the results of Chaney et al. (2004) who report negative estimates of s_{SBIG} (-0.167) and positive estimates of s_{SNON} (0.508). Of course, the fees represent willingness to pay for the particular services provided by each type of auditor as well as cost, so the results may merely indicate that big 4 auditees are willing to pay more for the services of big 4 and less to other auditors. Non big 4 auditees value each type of auditor differently from big 4 auditees; not only are they willing to pay more for the services of non big 4 auditors but they also place a lower value on the services of a big 4 auditor.

Although it is prima facie puzzling why firms do not change auditors, it is not implausible that companies choose more expensive auditors from both big 4 and non big 4 categories. As discussed earlier, there are numerous explanations in the auditing literature for firms paying higher fees for the appointment of big 4 auditors. Similarly, recent survey-based research by Marriott et al. (2007) finds that very small UK companies prefer non-big 4 auditors due to the more personal services and stronger relationships offered by smaller auditors, especially since the latter are often involved in the provision of other accounting services such as tax advice. Our MLE results in Table 3 imply that all of the difference in fees is due to unobservable auditee characteristics, making it difficult to acquire precise information about the potential cost savings and discouraging mobility. Moreover, each type of auditor can exploit the lack of mobility by raising fees so the positive selection effects may reflect in part monopoly rents for both types of auditor. A further possibility is that the potential gains involved in switching auditor may not justify the costs involved: for instance, the median fees paid by a big 4 auditee were £13,000 while the median sales were over £8m.

The results in Models 5a and 5b using the Heckman two-step estimator are somewhat perplexing since they exaggerate the MLE results. Although the coefficients on the l are significant at the 0.000 level for both equations, they are implausibly large (in absolute terms) at 0.446 for the big 4 and -0.509 for the non-big 4 auditees. Thus the selection coefficient for the big 4 equation more than doubles (compared to the MLE), leading to huge changes in the composition of the conditional mean for big 4 auditees. Further indications of model instability are provided by the insignificance of the intercept and QUALIF in the big 4 Heckman model (5b). Given these results and the reservations in the literature concerning the robustness of this technique in prior research, we subject this result to further scrutiny by assessing its sensitivity to changes in specification.

To calculate the impact of selection bias on the big 4 premium by isolating its observable and unobservable effects, we concentrate on the big 4 premium measured at the sample means of the big 4 auditees, i.e., the average effect of the treatment on the treated (*ATT*). The predicted audit fees paid by a big 4 client at the sample means are:

$$\overline{\ln F_{BIG4}} = a + b + \Sigma_k b_k \overline{X_{kBIG4}} + g_{SBIG} \overline{l_{BIG4,BIG4}} \qquad \text{For big 4 clients (actual)} \qquad 24.$$

$$\overline{\ln F_{NON}} = a + \Sigma_k a_k \overline{X_{kBIG4}} + g_{SNON} \overline{l_{BIG4,BIG4}} \qquad \text{For big 4 clients (counterfactual)} \quad 25.$$

The counterfactual equation (27) shows the predicted audit fees of a typical big 4 client if they were paid according to the non-big 4 equation. Since the same regressor means are used to compute predicted audit fees, we have removed any potential differences due to the different characteristics (the explained differences) of the big 4 and non-big 4 auditees, with any remaining difference amounting to the big 4 premium (the unexplained differences).

The two components of predicted audit fees estimate the separate effects of the observable regressors and the unobservables. For example, the decomposition for the counterfactual audit fees ($\overline{\ln F_{NON}}$) comprises the predicted fees paid to a non big 4 auditor by any firm with the same mean observable characteristics ($a + \Sigma_k a_k \overline{X_{kBIG4}}$) plus the selection effect ($g_{SNON} \overline{l_{BIG4,BIG4}}$) showing the predicted effect of unobservable characteristics. The first term is the unconditional mean showing the predicted audit fees if the allocation of clients to big 4 and non-big 4 auditors were random.[18] The predicted fees (ln*F*) incorporate the selection terms and are therefore referred to as the conditional

[18] Note that with random selection, there would be no selection effect.

means.[19] Hence, the predicted fee equations have the form: conditional mean = unconditional mean + selection effect.

The estimates for models 5a and 6a in Table 3 are:

$$\overline{\ln F_{BIG4}} = a + b + \Sigma_k b_k \overline{X_{kBIG4}} + g_{SBIG}\,\overline{l_{BIG4,BIG4}} \qquad \text{For big 4 clients (actual)} \qquad 26.$$

9.4364 = 9.2268 + 0.2096

And:

$$\overline{\ln F_{NON}} = a + \Sigma_k a_k \overline{X_{kBIG4}} + g_{SNON}\,\overline{l_{BIG4,BIG4}} \qquad \text{For big 4 clients (counterfactual)} \qquad 27.$$

8.8230 = 9.1174 - 0.2944

The typical big 4 auditee actually paid fees in natural log form of 9.4364 (£12,537). By contrast it would have paid predicted fees as a non big 4 auditee of 8.8230 in natural log form (£6,789) giving a very large big 4 premium of 0.6134 or 85%. Our results suggest that on average, big 4 auditees would have paid 9.2268 in natural log terms (£10,166) for the services of a big 4 auditor and 9.1174 (£9,113) for a non-big 4 auditor, if their unobservable characteristics were ignored. However, in consequence of the big 4 auditees' unobservable characteristics, an additional 0.2096 in log terms is paid for the services of a big 4 auditor, and 0.2944 less for the services of a non big 4 auditor (note that since the equations are estimated in natural log terms, they do not give a simple linear decomposition in pounds).

The conditional fee of £12,537 is obtained by multiplying the unconditional fee of £10,166 by the MLE selection effect 1.23 ($e^{0.2096}$). The effect of unobservables is to increase the unconditional big 4 fees in pounds by 23%. Similarly the effect of unobservables is to decrease the non big 4 fees in pounds by 26% ($e^{-0.2944}$=0.74). Big 4 auditees choose the more expensive auditors based on observed information. The effect of the unobservables drives the big 4 fees further above those of the smaller auditors.

The average treatment effect on the treated (*ATT*) is the difference in the conditional means of the audit fees paid by big 4 and non-big 4 auditees and represents the difference in fees that can only be

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19 They are conditional in the sense that they are estimates of the expected audit fees conditional on the firm employing either a big 4 or a non-big 4 auditor.

achieved by big 4 auditees. By contrast, the average treatment effect (*ATE*) shows the difference in fees available to any auditee. The relationship between the treatment effects is shown below:

$$\overline{\ln F_{BIG4,BIG4}} - \overline{\ln F_{NON,BIG4}} = b + \Sigma_k (b_k - a_k)\overline{X_{kBIG4}} + g_{SBIG}\,\overline{l_{BIG4,BIG4}} - g_{SNON}\,\overline{l_{BIG4,BIG4}} \qquad 28.$$

(*ATT*) = (*ATE*) + Estimate[E(e_{BIG4}|D=1)- E(e_{NON}|D=1)]

Change in conditional means = change in unconditional means + change in unobservable effect

9.4364-8.8230 = 9.2268-9.1174 + 0.2096+0.2944

0.6134 = 0.1094 + 0.504

The big 4 premium paid by big 4 auditees or *ATT* is 0.6134 (85%). The typical big 4 auditee paid 0.1094 (12%) more in fees based on their observable characteristics. This *ATE* is generally available in that any firm with the same characteristics could achieve these savings by switching auditor type. However the peculiar unobservable characteristics of big 4 auditees mean that they would pay 0.504 more in natural log terms for the services of a big 4 auditor, whereas the unobserved characteristics of non big 4 auditees means they would not be willing to pay this premium. Since the selection effects are individually significant, they should be included in the model. Although the *ATE* is rather large, it is not significantly different from zero (t=0.93 [p = 0.17]. By contrast the large selection effect is highly significant (t=4.20; p = 0.00).

According to our two-step results, therefore, firms with similar observable characteristics would pay higher fees if they used a big 4 auditor, but the difference is insignificant. However, auditees differ greatly in their unobserved characteristics and these differences help to generate the big 4 premium. Our data do not enable us to identify whether the unobserved differences arise because the audits and resulting costs differ in some unobserved fashion or because different firms place different values on the products provided by both types of auditors. We emphasise, however, that our results contrast sharply with those of Chaney et al. (2004), who report that it is the unobservable factors which make it *cheaper* for big 4 auditees to opt for big 4 auditors, rather than non-big 4 ones.

To explore these findings in greater detail, Table 4 summarises our results and because of reports in prior literature of multicollinearity in the two-step model, the final column reports the R^2 from a regression of the sample selection term (l) on the remaining regressors in the audit fee equations (Table 4, specification a). These are 0.986 and 0.854 for the big 4 and non-big 4 equations respectively, suggesting that even after including an identifying variable (CHTA) multicollinearity may still be a problem. Table 4 therefore also examines the consequences of moderate perturbations in the specification of the two-step model. We estimate a model without CHTA, similar to that reported in prior research, and also exclude lnSAL from the model. The latter has been argued to capture an important aspect of the audit (e.g., Pong and Whittington, 1994) and has been found significant in many empirical studies; however, it was not included in the model reported by Chaney et al. (2004).

Insert Table 4 about here

Specifications a, c and e use MLE while specifications b, d and f follow previous studies and estimate the models using the standard Heckman two-sep procedure. The Heckman two-step results in Table 4 show that the typical big 4 auditee actually paid fees (in natural log terms) of 9.4364 (£12,537). By contrast it would have paid predicted fees as a non big 4 auditee of 8.2635 (£3,880) estimating the big 4 premium at 1.1729 or 223%. Big 4 auditees would have paid (in natural log terms) 8.7761 (£6,478) for the services of a big 4 auditor and 9.0180 (£8,250) for a non-big 4 auditor, if their unobservable characteristics were ignored. However, in consequence of the big 4 auditees' unobservable characteristics, an additional 0.6603 in natural log terms is paid for the services of a big 4 auditor, and 0.7545 less for the services of a non big 4 auditor. The effect of unobservables is to increase the big 4 fees in pounds by 94% ($e^{0.6603}$=1.94). According to these results, big 4 auditees choose the cheaper auditor based on observed information, but the most expensive when unobservable characteristics are taken into account.

To examine the role of the identifying variable, specifications c and d show the impact of excluding CHTA from the probit model. In this instance, changes in the MLE estimates are relatively minor, with the premium paid by the big 4 increasing moderately from 0.6134 (85%) to 0.6239 (87%).

The difference in unconditional means (*ATE*) in the Heckman model, however, increases almost fivefold to -1.155 and is now statistically significant ($p < 0.01$), though this is more than offset by the estimated impact of the unobservable selection difference (2.4845). Comparing specifications therefore suggests the Heckman results are highly sensitive to model specification using the standard approach, though this is apparently less problematic using ML.

Since it is inadvisable to rely on non-linearity for identification, we exclude sales (lnSAL) and contigent liabilities (CONLIAB) since they are both insignificant in the big 4 selection equation. However, excluding them from the selection equation produces little change in the estimates. The selection estimate for the big 4 audit fee equation is now insignificant for both the MLE and Heckman results (although it remains highly significant and negative for the non big 4 equation). The main implication for the MLE results is that the *ATE* is larger and the selection effect is smaller and insignificant. Once again the Heckman results are dramatically different from specification (b). The *ATE* is now positive because of the large fall in the selection effect in the big 4 audit fee equation although the difference in the selection effects continues to be substantial and the premium (*ATT*) is very large.

To summarise the findings in Table 4, if the Heckman model is correctly specified, the MLE appear to be the most efficient. Significant selection effects are found in our preferred specification (a) though the results differ substantially from those reported by Chaney et al. (204). Omitting the instrument in specification (c) suggests that multicollinearity may not be a serious practical problem with MLE but prior research suggests that the difference in the estimates between MLE and Heckman may itself be a sign of fragility. The Heckman estimates are therefore sensitive to the use of a satisfactory instrument: the lack of an instrument leads to an implausible change in the estimates. The remaining specifications in Table 4 emphasise the role of size in defining these results. The results are sensitive to the omission of sales but the unambiguous importance of sales in the fee equations and in prior theoretical and empirical research demonstrate that it should not be excluded. Overall, therefore, although the Heckman Two Step procedure is the most popular method for dealing with selection bias in the accounting literature, the estimates it provides are potentially seriously unstable.

We also test the sensitivity of selection effects by changing the samples included in the selection models in Table 5. Consider the case of a big 4 auditee that has a small probability on the basis of its observed characteristics of appointing a big 4 auditor. The selection term in the big 4 equation (l_{BIG4}) will be large and, perhaps counter-intuitively, this type of firm is not useful for identification because the selection term is mostly non-linear for small values for l_{BIG4}. Excluding firms with large values of l_{BIG4} may actually reduce the potential influence of multicollinearity. Similarly, a non big 4 auditee is behaving uncharacteristically if it chooses a non big 4 auditor when the probability of doing so is very low given its observed characteristics. We therefore examine whether our selection results are sensitive to the exclusion of extreme values of the probability of regime choice (or equivalently in the value of the selection term).

Insert Table 5 about here

Table 5 reports ML estimates of the coefficients of the sample selection terms as the sample changes. Row 1 reports (for comparison) our previous estimates based on samples containing all big 4 and all non big4 firms. Rows 2 and 3 reports estimates where the sample of big 4 auditees excludes firms with a small probability of choosing a big 4 auditor on the basis of their observed characteristics). The 5th percentile is the value for the probability (in this case 0.022) where 5% of big 4 auditees have a probability of choosing a big 4 auditor (Pr(D=1)) that is less than or equal to the 5th percentile (or 95% of big 4 auditees have Pr(D=1)>0.022). The 10th percentile is the value for the probability (0.041) such that 10% of big 4 auditees have Pr(D=1)≤0.041 and 90% have Pr(D=1)>0.041. The first results (rows 1-3) include all non big 4 auditees. Rows 4 and 5 apply the previous logic to the samples of non big 4 auditees. Row 6 excludes big 4 auditees with the largest and smallest probabilities of choosing a big 4 auditor on the basis of their observed characteristics. This appears reasonable on the grounds that they are atypical though these firms are likely to have values of the selection term lying in the range of values that is most useful for identification. Rows 7 and 8 extend this logic, firstly, to the sample of non big 4 auditors and, secondly, to a narrower range of observations.

The results in rows 1 to 5 suggest that selection remains important. Selection into the big 4 regime is just significant with a coefficient in the range 0.06 to 0.14. The estimates for selection into the big 4 regime are not well defined when the firms with the largest probabilities are excluded. This is perhaps unsurprising because the selection term becomes non-linear for large values of the probability and the sample size is no longer large enough to produce robust estimates. In summary the selection into non big 4 auditor selection is well defined. The selection coefficient for big 4 auditor appointments is, however, less robust when similar firms are included in the sample. Selection into the non big 4 group is always highly significant with a coefficient in the range -0.20 to -0.25. The results for selection into the non-big 4 regime may be similar because the very large sample sizes outweigh the effect of the high correlation between the selection term and the regressors in the fees model.

Matching Results

Because of the sensitivity of the Heckman model demonstrated above, this section reports the results of our matching analysis, which is not prone to the problems associated with model identification and specification. As discussed in more detail above, we employ two matching methods: propensity score matching, which is becoming increasingly popular in the social science and econometrics literature (e.g. Black and Smith, 2004; Simonsen and Skipper, 2006) and pre-process matching, as proposed by Ho et al. (2007).

Propensity Score Matching

As discussed above, recent developments in the statistics and econometrics literature have suggested propensity score matching as an additional or alternative approach to two-step Heckman procedures. Starting with the seminal paper of Rosenbaum and Rubin (1983), propensity score matching has received considerable attention in research where selection issues are potentially problematic. The ‘curse of dimensionality’, which makes matching increasingly difficult as additional dimensions (variables) are added to match on, is avoided, since big 4 auditees are matched with non-big 4 auditees on the basis of the predicted probabilities from a probit model where the dependent variable is the binary auditor choice outcome. Hence, in our study, big 4 auditees are matched to non-big 4 auditees on the basis of the predicted probability of employing a big 4 auditor – with the propensity scores (predicted probabilities) being derived from the probit selection equation (Model 4, Table 3), which includes all the explanatory variables listed in Table 1.[20]

The commonest propensity score matching method is nearest neighbour matching with or without calliper matching – where the calliper method imposes a maximum difference between the propensity score of the nearest neighbour matched observations. When employing this method, one faces a choice of whether to use replacement observations in the non-big 4 (non-treated) sample for matching with the big 4 (treated) sample. This can be important in the nearest neighbour (without calliper) approach, since very large big 4 clients may have a limited number of counterparts in the non-big 4 sample; hence, excluding replacement can result in large differences in propensity scores between the matched observations.

Insert Table 6 about here

Table 6 therefore reports a number of matching approaches to illustrate the robustness of our results. It shows that the big 4 premium (the difference in the means of lnAFEE for the big 4 and non-big 4 sub-samples) is statistically significant at $p<0.01$ under each type of matching, ranging from 0.2531 (28.8%) with a calliper of 0.001 (column 4) to 0.3082 (36.1%) under the nearest neighbour method with no replacement in column 3. Moreover, as the statistics in column 5 demonstrate, even when big 4 and non-big 4 companies are very closely matched (with a maximum absolute difference[21] in propensity scores of only 0.0001), the premium (0.2613 or 29.9%) remains robust and is within the range of premiums reported in our previous empirical analysis.[22] The analysis in Table 6 is based on differences in the natural log of audit fee to facilitate comparison with our previous findings; however, we also conducted

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[20] The conditional mean independence assumption (CIA) is that the choice of regime (big 4 auditee or non-big 4 auditee) is not dependent on the regime once the matching variables (***Z***) are taken into account. This means in practice that the values of ***Z*** should not depend on the type of regime. We therefore use all the regressors in the fees equation as matching instruments (***Z***) and make the reasonable assumption that all the measured characteristics are pre-determined before the choice of auditor is made.

[21] Note the difference may be positive or negative, depending on whether the predicted probability of choosing a big 4 auditor is larger or smaller than its matched counterpart and hence absolute differences are utilised.

[22] Further analysis (unreported, but available on request) revealed that the two samples were also very similar in respect of each of the characteristics (variables) in the probit equation.

the matching analysis using untransformed audit fees (rather than logged fees) and obtained similar results.

On the basis of matched samples that are very similar in terms of their observed characteristics, therefore, we find strong evidence of a big 4 premium of a similar magnitude to that found in prior auditing studies employing OLS. Unlike those provided by the Heckman approach, these estimates are not sensitive to model specification. We acknowledge, however, that the additional robustness (and the fact that no assumptions are made about functional form in assessing the premium) comes at a cost: unobservable differences which may affect auditor choice are effectively assumed to be randomly distributed across the samples of big 4 and non-big 4 clients.

Pre-processed OLS Results

In applying the pre-processing method, we firstly partitioned our sample of 36,674 companies into portfolios (quantiles) on the basis of their actual size, risk and complexity[23] because these factors have been found to be particularly important determinants of both audit fees and auditor selection (e.g., see Simunic and Stein, 1996; Chaney et al., 2004). We created 40 equally sized portfolios based on sales (SAL), 40 equally sized portfolios based on return on total assets (RTA), 10 portfolios based on the number of subsidiaries (SUBS) and 11 portfolios based on the ratio of exports to sales (EXPSAL). Following this procedure, we split the above portfolio samples into companies audited by big 4 and non-big 4 auditors and then matched the two samples so that each individual big 4 auditee had an individual non-big 4 counterpart with similar size, risk and complexity characteristics.

A difficulty with this process is that many big 4 clients have a number of non-big 4 counterparts of similar size, risk and complexity. In order to circumvent this problem, we randomly selected (with

[23] Note that the pre-processing matching method can be a more demanding process than propensity score matching since the former involves matching on the basis of actual values for the control variables simultaneously, rather than on the basis of a composite score; that is, each big four firm has a non-big 4 counterpart that has similar observed size *and* risk *and* complexity characteristics. However, an advantage of propensity score matching is that, although it matches on the basis of only one variable, that variable (propensity score) is derived from information obtained from all the explanatory variables.

replacement) one match for each big 4/non-big 4 auditee. Following this process, we combined the non-big 4 auditee sample and the big 4 auditee sample and then re-estimated our standard regression equation (Model 1 in Table 3). Using the random selection procedure, we repeated this process 2,000 times and obtained a distribution of BIG4 regression coefficients and their associated (White's corrected) t-statistics. Each iteration involved samples of 1,828 big 4 auditees and 1,828 matched non-big 4 auditee counterparts (i.e., a total sample in each regression of 3656). Additional analysis (unreported but available on request) showed that the two (big 4 and non-big 4) auditee samples were very closely matched on the four matching variables with, with on average, none of their means differing significantly at $p < 0.05$.[24]

Insert Table 7 about here

Descriptive statistics from the 2,000 regressions for the BIG4 coefficient and White's corrected t-statistics are reported in Table 7. The table shows that in every case, the BIG4 coefficient was statistically significant and positive, ranging from 0.2724 (26.7%) to 0.3091 (36.2%), with the mean and median taking the same value of 0.2724 (31.3%). The distribution of t-statistics reveals that the BIG4 coefficient is consistently significant at $p < 0.01$. It is also interesting to note that the range of coefficients implies a premium in the range of 27% - 36%, which is within the range (16-37%) found in prior literature. Hence, the big 4 premium is persistent after closely matching on key auditee attributes (size, risk and complexity) and controlling for any remaining confounding influences via the use of OLS regression.

CONCLUSIONS

Since the seminal paper by Simunic (1980), a large number of studies have predicted and found that large auditors have commanded a premium for their services, possibly due to superior audit quality, 'deep pockets' and other reputational effects. However, important innovations in the literature by Ireland and

[24] For each iteration, we collected the p-value and t-statistic for mean differences between the big 4 and non-big 4 samples for the four matching variables and out of the 2,000 iterations, there were no significant differences (at $p < 0.05$) in the variables on which we matched. More specifically, the range and mean for the absolute t-statistics, respectively, of the four variables were 0.31-0.56 and mean of 0.44 for lnSAL; 0.17-1.90 and mean of 1.07 for RTA; 0.18-0.51 and mean of 0.34 for SQSUBS; and 0.02-0.04 with a mean of 0.04 for EXPSAL. We also repeated this procedure by controlling for both sales and total assets (together with SUBS, EXPSAL and RTA) and obtained similar results (though inevitably on a smaller sample).

Lennox (2002) and Chaney et al. (2004) have challenged findings based on OLS regressions including a binary indicator variable for large auditors. More specifically, the latter paper overturned much of the prior research by stating that given their firm specific characteristics, private UK companies that chose a big 5 auditor would have paid more had they chosen a non-big 5 auditor; thus leading to the conclusion that a large auditor premium does not exist and that the audit market is properly organised (ibid., p. 70).

Using a comprehensive sample of UK private firms, our results suggest that the Heckman procedure does not provide a panacea for estimating selection effects. In particular, Chaney et alia's (2004) finding that firms select the type of auditor that provides the cheapest service once unobservables are taken in account is unsupported by our analysis. Second, the Heckman two-step method increasingly used in contemporary auditing research can be highly sensitive to model specification: we find no evidence of selection in the big 4 fees equation when sales are omitted and the selection effect doubles when there is no identifying variable. Finally, our results are also sensitive to estimation technique. In particular the selection effect for the maximum likelihood estimates differs dramatically from that obtained by the standard Heckman two-step method.

We also find that big 4 (non-big 4) firms without similar counterparts in the non-big 4 (big 4) samples have an influential affect on our Heckman results. When we re-estimated the models in the 'common support' region – where big 4 and non-big 4 auditees have more similar characteristics – the big 4 premium persists, but the coefficient on the IMR loses statistical significance for big 4 firms, again indicating that extant results may be sensitive to specification and/or a small sub-set of highly influential observations.

When we employ a less restrictive and more robust matching approach to estimate the premium by comparing the audit fees for big 4 and non-big 4 auditees of a similar degree of size, risk and complexity, we find a persistent premium of a magnitude in line with that found in prior single-stage OLS audit fee studies. Taken together with previous research which finds that large auditors produce higher quality audits (e.g., Lennox, 1999; Blokdijk et al., 2006) our results suggest that conclusions from Heckman-based research that the big 4 premium vanishes once selection is allowed for should be treated with caution. Although the matching estimators we employ are highly robust to changes in model specification, unlike the Heckman approach they are (by definition) unable to take account of unobservable client characteristics. Although prior analytical research suggests unobservable factors such as insider knowledge of future cash flows may be important in determining auditor choice, there is considerable disagreement on the direction of this effect (cf. Titman and Trueman, 1986 and Datar et al., 1991). A possible avenue for further work may be to identify and obtain empirical proxies for these unobservable characteristics, and to include such variables in less sensitive methods such as matching analysis.

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TABLE 1

Variable Definitions

Label	*Definition*
lnAFEE	Natural log of audit fee (in £)
lnSAL	Natural log of turnover (in £)
lnTA	Natural log of total assets (in £)
SQSUBS	Square root of the number of subsidiaries
EXPSAL	Ratio of non-UK turnover to total turnover
QUALIF	Binary variable taking the value of 1 if company had qualified audit report, 0 otherwise
PBAL	Binary variable taking the value of 1 if company disclosed post-balance sheet event in accounts, 0 otherwise
CONLIAB	Binary variable taking the value of 1 if company disclosed contingent liabilities in accounts, 0 otherwise
EXITEM	Binary variable taking the value of 1 if company disclosed exceptional and/or extraordinary items in accounts, 0 otherwise
RTA	Ratio of profit before tax to total assets
TLTA	Ratio of total liabilities to total assets
LOND	Binary variable taking the value of 1 if company is located in London, 0 otherwise
BUSY	Binary variable taking the value of 1 if firm's year-end is in December or March, 0 otherwise
BIG4	Binary variable taking the value of 1 if company is audited by a big four auditor, 0 otherwise
CHTA	Absolute value of change in total assets from year t-1 to year t

TABLE 2

Descriptive Statistics

Variable	*Big 4 clients (n = 3,038)*			*Non Big 4 clients (n = 33,636)*			*Total sample (n = 36,674)*			
	Mean	*Std. dev.*	*Median*	*Mean*	*Std. dev.*	*Median*	*Mean*	*Std. dev.*	*Median*	*Sig.*
AFEE (£000)	29.05	80.47	13.00	5.88	13.12	2.75	7.80	27.11	3.00	‡§
SAL (£m)	39.41	150.62	8.14	5.13	21.46	0.84	7.97	48.89	1.02	‡§
TA (£m)	35.62	159.41	6.08	3.17	14.49	0.48	5.86	48.75	0.59	‡§
SUBS	3.46	8.37	1.00	0.61	2.46	0.00	0.84	3.46	0.00	‡§
EXPSAL	0.08	0.20	0.00	0.02	0.12	0.00	0.03	0.13	0.00	‡§
QUALIF*	0.04	0.19	0.00	0.03	0.17	0.00	0.03	0.18	0.00	
PBAL*	0.12	0.33	0.00	0.04	0.19	0.00	0.04	0.21	0.00	ψ
CONLIAB*	0.27	0.45	0.00	0.10	0.30	0.00	0.11	0.31	0.00	ψ
EXITEM*	0.57	0.50	1.00	0.32	0.47	0.00	0.34	0.47	0.00	ψ
RTA	0.01	0.38	0.03	0.23	0.78	0.07	0.21	0.76	0.07	‡§
TLTA	0.84	1.51	0.73	0.77	1.15	0.66	0.78	1.18	0.67	‡§
LOND*	0.21	0.41	0.00	0.34	0.47	0.00	0.33	0.47	0.00	ψ
BUSY*	0.56	0.50	1.00	0.44	0.50	0.00	0.45	0.50	0.00	ψ
CHTA (£m)	5.26	33.82	0.61	0.49	2.71	0.05	0.88	10.16	0.06	‡§

Notes:
‡ and § indicate means and distributions are significantly different between big 4 and non-big 4 clients at the 0.01 level in t-tests and Mann-Whitney tests respectively.
ψ indicates significant difference between big 4 and non-big 4 clients at the 0.01 level in a chi-squared test.
* Signifies a binary variable for which the mean describes the proportion of the sample taking a value of unity

TABLE 3
Regression Results

	OLS Single Stage Models			*MLE Two Step Models*			*Heckman Two Step Models*		
	Model 1 (Pooled)	*Model 2 (Big 4)*	*Model 3 (Non-big 4)*	*Model 4a (Probit)*	*Model 5a (Big 4)*	*Model 6a (Non-big 4)*	*Model 4b (Probit)*	*Model 5b (Big 4)*	*Model 6b (Non-big 4)*
lnSAL	0.284 (87.31)**	0.285 (25.08)**	0.286 (83.84)**	-0.004 (0.48)	0.285 (30.93)**	0.286 (96.44)**	-0.005 (0.50)	0.285 (29.51)**	0.285 (92.71)**
lnTA	0.122 (36.28)**	0.120 (10.30)**	0.120 (33.54)**	0.246 (23.25)**	0.149 (8.00)**	0.113 (34.86)**	0.246 (23.20)**	0.211 (5.41)**	0.101 (25.46)**
SQSUBS	0.258 (44.70)**	0.201 (19.07)**	0.281 (40.10)**	0.087 (6.98)**	0.209 (19.81)**	0.268 (46.05)**	0.088 (7.03)**	0.227 (15.28)**	0.247 (34.78)**
EXPSAL	0.367 (13.15)**	0.627 (10.91)**	0.293 (9.41)**	0.607 (9.84)**	0.688 (11.34)**	0.253 (8.98)**	0.602 (9.77)**	0.822 (8.36)**	0.191 (6.17)**
QUALIF	0.115 (6.18)**	0.141 (2.56)*	0.111 (5.58)**	-0.146 (2.61)**	0.126 (2.30)*	0.118 (6.06)**	-0.146 (2.61)**	0.094 (1.57)	0.128 (6.36)**
PBAL	0.119 (7.74)**	0.179 (5.65)**	0.098 (5.62)**	0.169 (4.23)**	0.196 (5.85)**	0.084 (4.69)**	0.169 (4.23)**	0.233 (5.62)**	0.063 (3.34)**
CONLIAB	0.095 (8.93)**	0.064 (2.64)**	0.099 (8.47)**	0.014 (0.48)	0.064 (2.57)*	0.096 (7.68)**	0.013 (0.45)	0.066 (2.45)*	0.091 (7.09)**
EXITEM	0.131 (17.04)**	0.126 (5.57)**	0.130 (15.88)**	-0.081 (3.38)**	0.118 (5.06)**	0.133 (16.14)**	-0.080 (3.35)**	0.100 (3.78)**	0.137 (15.99)**

TABLE 3 (continued)

RTA	-0.033 (7.14)**	-0.111 (3.28)**	-0.031 (6.65)**	-0.231 (8.12)**	-0.139 (3.87)**	-0.031 (6.82)**	-0.230 (8.10)**	-0.199 (4.02)**	-0.032 (6.54)**
TLTA	0.026 (6.43)**	-0.009 (1.31)	0.029 (6.24)**	0.076 (9.07)**	-0.004 (0.48)	0.025 (8.04)**	0.076 (8.98)**	0.007 (0.59)	0.019 (5.38)**
LOND	0.208 (29.69)**	0.338 (12.38)**	0.200 (27.63)**	-0.306 (12.15)**	0.306 (9.93)**	0.210 (29.10)**	-0.305 (12.11)**	0.237 (4.72)**	0.226 (27.93)**
BUSY	0.011 (1.76)	0.010 (0.52)	0.010 (1.51)	0.153 (7.12)**	0.026 (1.18)	0.004 (0.63)	0.152 (7.10)**	0.0601 (2.01)*	-0.005 (0.65)
BIG4	0.270 (22.96)**								
CHTA				0.007 (4.17)**			0.007 (4.27)**		
IMR (λ) (s_{SBIG} or s_{SNON})					0.142 (1.80)	-0.199 (9.56)**		0.446 (2.42)**	-0.509 (8.39)**
CONSTANT	2.299 (88.49)**	2.638 (23.07)**	2.302 (83.80)**	-4.886 (46.58)**	1.967 (5.14)**	2.378 (87.60)**	-4.870 (46.62)**	0.511 (0.58)	2.499 (69.11)**
Observations	36674	3038	33636	36674	3038	33636	36674	3038	33636
Adj. R-squared	0.78	0.80	0.75					0.80	0.75

Notes:
* and ** indicate significance at 5% and 1% respectively. The absolute value of the *t*-statistic is shown in parentheses. The probit estimates for the ML models are for the big 4 selection model. For Models 4b-6b, z-statistics are in parentheses (based on the method proposed by Greene (1981) for Models 5 & 6).

TABLE 4

Effects of Changes in Specification on Heckman Two-Step Models

Specification†		*Cond. Mean or Difference* (=*ATT*)	*Uncond. Mean or Difference* (=*ATE*)	*Selection Effect*	*Coefficient of Selection Term* (l) (s_{SBIG}/s_{SNON})	$R^{2\,§}$
Preferred						
a. MLE	*Big 4*	9.4364	9.2268	0.2096	0.142	0.986
					(1.80)	
Fees: Full model	*Non-Big 4*	8.8230	9.1174	-0.2944	-0.199	0.854
					(9.56)**	
Probit: Full model	*Difference*	0.6134	0.1094	0.5040		
			(0.93)	(4.20)**		
b. Heckman	*Big 4*	9.4364	8.7761	0.6603	0.446	0.986
					(2.42) *	
Fees: Full model	*Non-Big 4*	8.2635	9.0180	-0.7545	-0.509	0.858
					(8.39) **	
Probit: Full model	*Difference*	1.1729	-0.2419	1.4148		
			(-0.88)	(4.92)**		
No identifying variable						
c. MLE	*Big 4*	9.4364	9.1898	0.2465	0.166	0.992
					(2.31)*	
Fees: Full model	*Non-Big 4*	8.8125	9.1154	-0.3029	-0.204	0.868
					(10.00)**	
Probit: Excludes (CHTA)	*Difference*	0.6239	0.0744	0.5495		
			(0.69)	(4.95)**		
d. Heckman	*Big 4*	9.4364	7.8345	1.6019	1.079	0.992
					(3.74)**	
Fees: Full model	*Non-Big 4*	8.1070	8.9895	-0.8825	-0.595	0.874
					(9.22)**	
Probit: Excludes (CHTA)	*Difference*	1.3294	-1.1551	2.4845		
			(-2.69) **	(5.66)**		
No Sales variable						
e. MLE	*Big 4*	9.4364	9.3588	0.0776	0.052	0.986
					(0.45)	
Fees: Exc. lnSAL	*Non-Big 4*	8.8845	9.1174	-0.2330	-0.157	0.854
					(7.12)**	
Probit: Exc. lnSAL, Conliab	*Difference*	0.5520	0.2414	0.3106		
			(1.38)	(1.76)		
f. Heckman	*Big 4*	9.4364	9.2961	0.1404	0.095	0.986
					(0.51)	
Fees: Exc. lnSAL	*Non-Big 4*	7.8456	8.9330	-1.0874	-0.734	0.857
					(10.89)**	
Probit: Excludes lnSAL, Conliab	*Difference*	1.5909	0.3631	1.2278		
			(1.30)	(4.14)**		

Notes: Differences ATT=ATE+Selection Effect.

†The figures in parenthesis in the columns labelled ‘conditional’ and ‘unconditional’ are the t-values for the difference in predicted log fees. In the case of MLE we could only extract the information for the computation of the variance-covariance matrix for the difference in the unconditional means.

‡ The figures in parentheses in the column ‘selection effect’ are *t*-values for the estimate of the coefficient of the selection term.

§ The column labelled R^2 shows the R^2 for a regression of the l on the remaining regressors in the fees equation.

TABLE 5

Effects of Changes in Sample on Heckman Models

Row	*Sample definitions*		*Lambda*	
	Pr(Big 4=1)	*Pr(Non Big4=1)*	*Big 4*	*Non Big4*
1.	All	All	0.142 (1.80)	-0.199 (9.56)**
2.	Largest 95%	All	0.133 (1.66)	-0.231 (12.60)**
3.	Largest 90%	All	0.144 (1.82)	-0.247 (14.22)**
4.	Largest 95%	Largest 95%	0.100 (2.31)*	-0.229 (11.58)**
5.	Largest 90%	Largest 90%	0.063 (2.07)*	-0.212 (9.36)**
6.	Middle 90%	All	-0.009 (-0.09)	-0.238 (13.27)**
7.	Middle 90%	Middle 90%	0.053 (0.98)	-0.225 (10.34)**
8.	Middle 80%	Middle 80%	0.022 (0.45)	-0.216 (8.37)**

Notes:
t-values are in parentheses
**, * represent statistical significance at the 0.01 and 0.05 level respectively
All models use the full model specification (see Table 3) for the probit and audit fee equations.

TABLE 6
Propensity Score Matched Results†

	Nearest Neighbour (with replacement)	*Nearest Neighbour (no replacement)*	*Caliper of 0.001 (absolute difference in p-score)*	*Caliper of 0.0001 (absolute difference in p-score)*
Mean difference	0.2642	0.3082	0.2531	0.2613
Big 4 premium‡	30.2%	36.1%	28.8%	29.9%
z-statistic	8.23**	15.58**	12.54**	10.91**
N§	6076	6076	5586	4814
Mean absolute difference in p-score	0.0003	0.2393	0.0001	0.0000
Minimum absolute difference in p-score	0.0000	0.0000	0.0000	0.0000
Maximum absolute difference in p-score	0.3960	0.6848	0.0010	0.0001

Notes
† The probit selection model from which propensity scores (p-scores) are derived is reported in Table 3 (Model 4).
‡ Results are based on bootstrapped standard errors (50 replications). Premium is the difference between the mean lnAFEE for big 4 auditors minus the mean lnAFEE for their matched big 4 counterparts.
§ Note that each method results in an equal number of matched big 4 and non-big 4 auditees.
** represents statistical significance at the 0.01 level

TABLE 7

Pre-processed Portfolio Matched Regression Results

	Mean	*Std. Dev.*	*Median*	*Min*	*Max*
BIG4 coefficient†	0.2724	0.0114	0.2724	0.2369	0.3091
Big 4 premium‡	31.3%	-	31.3%	26.7%	36.2%
BIG4 *t*-statistic	13.73	0.5652	13.73	11.98	15.51
F-Value	832.58	30.15	833.24	717.57	926.04
Adjusted R^2	0.7679	0.0040	0.7679	0.7544	0.7792

Notes

† Big4 coefficient is the estimated coefficient from each iteration of a random sample of companies matched on the basis of sales (40 portfolios), exports to sales (11 portfolios), return on total assets (40 portfolios) and the number of subsidiaries (10 portfolios) from Model 1, Table 3. The number of portfolios for the ratio of exports to sales and number of subsidiaries differs due to a large number of zero values for each variable.

‡ Based on 2000 iterations where each iteration involves a regression on a total sample of 3,656 companies (i.e., 1,828 big 4 and 1,828 non-big4 auditees). The t-statistic in each iteration is based on White's (1980) correction for heteroskedasticity.