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Are large auditors more accurate than small auditors?

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Abstract—Theoretical research suggests that large auditors have more incentive to issue accurate reports compared to small auditors (DeAngelo, 1981; Dye, 1993). Controlling for the client characteristics of large and small auditors, this paper shows that large auditors issue reports that are more accurate and more informative signals of financial distress. These findings are consistent with the theoretical prediction of a positive relationship between auditor size and auditor accuracy.

1. Introduction

Existing theories predict that large auditors have more incentive to issue accurate reports.[1] Reputation arguments suggest that large auditors suffer a greater loss of rents as a result of inaccurate reporting (DeAngelo, 1981). Moreover, auditors have more incentive to give accurate reports, the greater is the litigation penalty that is suffered for inaccuracy (Dye, 1993). Since large auditors have deeper pockets than small auditors, they should have more incentive to issue accurate reports.[2]

Much empirical evidence indicates that large audit firms are associated with higher quality. Large auditors tend to receive higher fees than small auditors (Simunic and Stein, 1987; Beatty, 1989); in IPOs, high reputation investment banks prefer their clients to hire large auditors, and companies that do hire large auditors are charged a smaller banking fee (Menon and Williams, 1991; Balvers et al., 1988). These results suggest that large auditors offer higher quality services; however, quality is not really the same thing as accuracy. Large auditors may give a higher quality service, but this does not necessarily mean that large auditors are more accurate.

Theories on auditor selection have argued that a company has more incentive to hire an accurate auditor when it has favourable information and when agency costs are high. This is because an accurate auditor is more likely to attest to the company's private information and because hiring an accurate auditor can be a signal to investors that the company has favourable private information (Titman and Trueman, 1986; Datar et al., 1991). Empirical studies have tested these theories by examining the stock market reaction to different types of auditor switch and by examining the relationship between agency costs and auditor choice. If companies with favourable private information prefer to hire large auditors, the stock market should react more favourably when companies switch to large auditors than to small auditors.

Some studies have found that the stock market reacts in the hypothesised direction (Nichols and Smith, 1983; Eichenseher et al., 1989); other studies have found no significant difference in market reaction for different types of switch (Firth and Smith, 1992; Johnson and Lys, 1990; Schwartz and Soo, 1995). Unfortunately, the event study approach is not a useful way of testing whether large auditors are more accurate, because a switch to a large (small) auditor may signal good (bad) news for reasons that have nothing to do with accuracy. In particular, a company may switch to a large (small) auditor if it is expecting to grow (decline). Thus, the stock market reaction may reflect a com-

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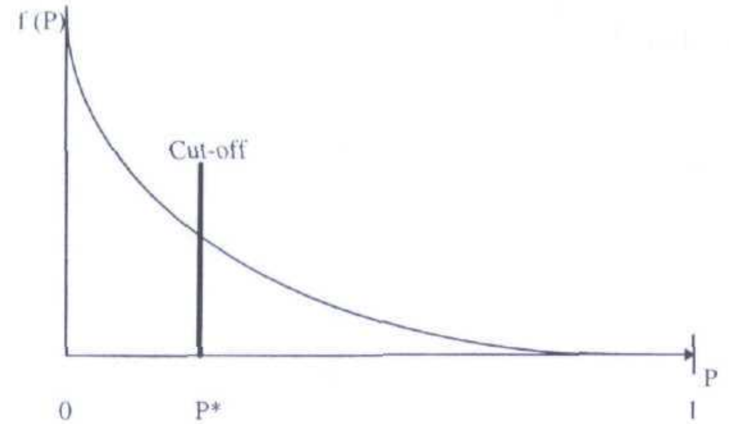
[1] Between 1987–94, the large UK audit firms were known as the 'Big Six', comprising Price Waterhouse, KPMG Peat Marwick, Arthur Andersen, Touche Ross, Coopers & Lybrand and Ernst & Young. All other audit firms are referred to as small in this paper.

[2] Large audit firms have deeper pockets than small audit firms because of joint and several liability. The *Economist* writes (7 October, 1995): 'As partnerships, the large accountancies operate under the legal principle of joint and several liability. This means that when a company collapses, its auditors who not only have deep pockets, but cannot abscond, may be hit for the entire bill if they were negligent, even if other parties were careless too. Moreover, if the claim amounts to more than an auditing firm's capital, all of the firm's partners are liable right down to their bootstraps for the bill—even if they had nothing to do with the error.' Similarly, the *Financial Times* writes (4 July, 1996): 'The big audit firms can find themselves targeted for lawsuits because of their "deep pockets"—including their statutory insurance cover.'

Figure 1
An auditor's expectations about its clients' bankruptcy probabilities



pany's product market opportunities rather than differential accuracy between auditors. Studies have generally confirmed the predicted relationship between agency costs and auditor choice—companies with high agency costs are more likely to hire large auditors (Francis and Wilson, 1988; Johnson and Lys, 1990; DeFond, 1992). Although this is consistent with the view that large auditors are more accurate, there is an alternative explanation—managers may simply value the prestige that comes from being associated with large auditors in much the same way as they might value non-profit-maximising profits.

In contrast to these studies, this paper directly investigates the relationship between auditor accuracy and auditor size. Using a bankruptcy model to control for differences in client characteristics, it shows that large auditors' reports are significantly more accurate indicators of financial distress compared to small auditors' reports. The next section describes the methodology used to evaluate the accuracy and informativeness of audit reports. The following sections describe the data and present the results.

2. Research methodology

2.1. Evaluating the accuracy of audit reports

In evaluating the accuracy of audit reports, it is helpful to consider Figure 1. The horizontal axis shows an auditor's expectations about its clients' bankruptcy probabilities (P); the vertical axis shows the density function f(P). Figure 1 illustrates the case where most companies have low expected bankruptcy probabilities. An auditor is assumed to choose a 'cut-off probability' P*, which determines the number of companies that are given qualified reports; companies with low bankruptcy probabilities (those lying to the left of P*) are given unqualified reports while companies with high bankruptcy probabilities (those lying to the right of P*) are given qualified reports.

The main difficulty in measuring the accuracy of audit reports is that one does not directly observe whether companies deserve clean or qualified audit opinions. Therefore, previous research has used the bankruptcy outcome as an ex post measure of whether a company should have been given a qualified report. This approach is not a perfect measure of accuracy—for example, a company could enter bankruptcy after being given an unqualified report if there were no obvious problems when the audit was undertaken; similarly, a company could survive following a qualified report even if there were clear financial problems. Therefore, previous research has used bankruptcy models as a benchmark for evaluating the accuracy of audit reports (Altman and McGough, 1974; Koh, 1991).

For financially distressed companies that survive, the bankruptcy model is likely to predict bankruptcy and the auditor may qualify; similarly, for companies that are apparently healthy prior to failure, the bankruptcy model may incorrectly predict survival and the auditor is likely to give an unqualified report. If bankruptcy is difficult (easy) to predict, one would expect error rates to be high (low) for both the model and auditors. If auditors have access to private information that is useful for identifying failing companies, one might expect audit reports to be more accurate than the model. If audit reports are affected by factors other than the probability of bankruptcy, one might expect audit reports to be less accurate than the model.

This paper compares the accuracy of audit reports and a bankruptcy model by measuring two errors. Following Koh (1991), the type I error rate is equal to the proportion of failing companies that are given unqualified reports and the type II error rate is equal to the proportion of non-failing companies that are given qualified reports.[3] Practitioners might argue that Koh's definition of a type II error is problematic, since a qualified report signals a potential problem rather than predicts bankruptcy. The reason for calculating both type I and type II errors is best explained by considering an extreme case, where an auditor always gives qualified reports (i.e. the auditor chooses $P^*=0$). If one ignored type II errors and simply measured accuracy in terms of type I errors, one would have the misleading impression that this uninformative reporting strategy maximises accuracy.

Calculating both type I and type II errors helps clarify an important distinction between the accuracy and conservatism of auditors. For a given distribution of bankruptcy probabilities, an increase in auditor conservatism raises the frequency of qualified reports (a more conservative auditor chooses a lower P^*). Therefore, a more conservative auditor has lower type I and higher type II error rates for a given level of accuracy. On the other hand, a more accurate auditor has lower type I and type II error rates, for a given level of conservatism (i.e. for a given choice of P^*).

2.2. Evaluating the incremental information content of audit reports

In addition to measuring the accuracy of audit reports, it is useful to test whether reports signal useful incremental information about the probability of bankruptcy (Hopwood et al., 1989). The accuracy of audit reports is not necessarily related to their incremental information content. For example, auditors might give going-concern qualifications (clean opinions) when their private information is less (more) favourable than public information (Grout et al., 1994). In this view, audit opinions are used to signal auditors' private information and do not fully reflect all public information. Thus, it is theoretically possible that the incremental information content of audit reports could be high (low) even if accuracy is low (high). The role of public and private information is shown in equations (1) and (2):

$$FAILS_{it}^* = \beta_0+\beta_1X_{it}+\beta_2Z_{it}+u_{1it} \quad (1)$$

$$GQ_{it}^* = \gamma_0+\gamma_1X_{it}+\gamma_2Z_{it}+u_{2it} \quad (2)$$

where:

$FAILS_{it}$ = 1 if company i issues its final annual report in year t prior to entering bankruptcy;
= 0 otherwise. $FAILS_{it}^* \geq 0$ if $FAILS_{it}=1$; $FAILS_{it}^* < 0$ if $FAILS_{it}=0$.

GQ_{it} = 1 if company i receives a going-concern qualification in year t; = 0 otherwise. $GQ_{it}^* \geq 0$ if $GQ_{it}=1$; $GQ_{it}^* < 0$ if $GQ_{it}^*=0$.

X_{it} = Publicly observable variables capturing financial health.

Z_{it} = Privately observable variables capturing financial health.

Equation (1) states that the likelihood of failure depends on variables that capture the financial health of the company. Some of these variables are publicly observable (X_{it}); others are observable to the auditor but not publicly observable (Z_{it}). Equation (2) allows audit reporting to depend on the financial health of companies (X_{it} and Z_{it}). It is assumed that $E[u_{1it}\ u_{2it}]=0$. This makes sense because there is usually a lag of several months between the audit reporting decision and the bankruptcy event.

One would like to test whether audit reports signal valuable private information about the probability of bankruptcy. However, one cannot directly test the null hypothesis $\gamma_2=0$ because the statistician does not observe Z_{it}. This problem can be circumvented by including the audit report variable (GQ_{it}) in the bankruptcy model as shown in equation (3):

$$FAILS_{it}^* = \beta_0+\beta_1X_{it}+\beta_3GQ_{it}+v_{it} \quad (3)$$

Under the null hypothesis that audit reports do not signal valuable private information about the probability of bankruptcy, $\gamma_2\beta_2=0$. If $\gamma_2\beta_2=0$ it must also be true that $E[GQ_{it}\ v_{it}]=0$, which implies that $\beta_3=0$. If reports do not signal valuable private information about the probability of bankruptcy, audit reports should not be useful for predicting bankruptcy after controlling for all publicly observable financial distress variables (X_{it}). Under the alternative hypothesis, a going-concern qualification is a signal of financial distress ($\gamma_2\beta_2>0$) and audit reports should be useful for identifying failing companies ($\beta_3>0$). Under the null hypothesis that large and small auditors' reports are equally informative, one should be unable to reject the null hypothesis that β_3 is the same for large and small auditors. Under the alternative hypothesis, large auditors' reports have greater incremental information content and β_3 is signifi-

[3] This does not imply that a qualified report is necessarily equivalent to a prediction of bankruptcy. For example, if an auditor chooses a P^* which is less than 0.5, qualified reports would be given to companies which the auditor believes are more likely to survive than fail. Table 5 shows that, on average, large (small) auditors give going-concern qualifications to companies whose bankruptcy probabilities exceed 18% (15%).

cantly more positive for large auditors than for small auditors.

3. Data

3.1. The sample

An attempt was made to collect data on all publicly quoted UK companies between 1987–94.[4] For failing companies, data were collected from all accounts published from 1987 until the first public announcement of failure; for non-failing companies, data were collected in all available years between 1987–94.[5]

Firstly, information on companies' auditors and audit reports was collected from microfiche copies of companies' annual reports.[6] From each report, it was noted whether the auditor had given a qualified or unqualified audit opinion. When there is a significant possibility of the company ceasing to trade in the foreseeable future, the auditor is required to state that the accounts give a true and fair view subject to the company remaining a going concern. The 'Auditing Guideline on Going Concern' (August 1985) states: 'The going concern concept identified in Statement of Standard Accounting Practice No. 2 is "that the enterprise will continue in operational existence for the foreseeable future". This means in particular that the profit and loss account and the balance sheet assume no intention or necessity to liquidate...The foreseeable future should normally extend to a minimum of six months following the date of the audit report or one year after the balance sheet date whichever periods ends on the later date.'

In the sample, qualifications were given for fundamental uncertainties and non-compliance with Statements of Standard Accounting Practice (SSAPs) as well as for going-concern reasons.[7] Failing companies that received qualified reports more than one year prior to failure were included in the analysis so as to calculate type I and type II error rates for alternative bankruptcy horizons.[8] A list of companies that entered administration, receivership or liquidation was obtained from Stock Exchange Financial Yearbooks.[9] All such companies are defined in this paper as failing. Microfiche data were available for 1,086 companies of which 123 failed between 1987–94.

[4] A UK company is so defined if its headquarters and auditor were based in the UK. Many of the companies in the sample had overseas operations and overseas shareholders.

[5] There were no cases where failing companies issued accounts after the first public announcement of failure.

[6] These are located in the Corporate Information Library at Warwick University. Data on companies that were taken over were collected up to the point of takeover, and thereafter these companies were treated as missing observations.

[7] 'Fundamental uncertainties' arose where auditors were uncertain about provisions made for tax, slow-moving stocks, bad debts or litigation—72 companies received qualified reports for issues other than going-concern while 17 companies received reports that were qualified for both going-concern and non-going-concern issues. The former were coded with a zero, while the latter were coded with a one.

[8] For example, a qualification two periods prior to failure is classified as a type II error when the bankruptcy horizon is one period and is classified as an accurate report when the horizon is two or more periods. Longer bankruptcy horizons have the disadvantage that there is a greater probability of mis-classifying a type II error as an accurate report. As shown in Table 2, the conclusions of this study are not sensitive to different bankruptcy horizons.

[9] In the UK, there are three types of reorganisation procedure when a company becomes insolvent—liquidation, receivership and administration. In a liquidation, the assets of the company are sold so as to meet the claims of creditors. In a receivership, the receiver can decide whether it is in the creditors' interests to sell the company's assets. Generally, it is in the creditors' interests to liquidate if the liquidation value of the company exceeds its going concern value. The possibility of administration was introduced by the 1986 Insolvency Act in an attempt to reduce the number of inefficient liquidations. However, few administrators have been appointed compared to the numbers of companies entering receivership or liquidation. The results in this paper are not sensitive to different kinds of reorganisation procedures.

Table 1
Financial health and audit reporting (1987-94)

	1987	*1988*	*1989*	*1990*	*1991*	*1992*	*1993*	*1994*	*Total*
S_t	799	862	903	927	925	908	897	883	7,104
F_t	4	5	6	36	46	41	15	7	160
$NFAILS_t$	5	13	31	35	26	8	3	2	123
NGQ_t	1	3	3	20	27	26	22	21	123

S_t = Number of observations in year t for which microfiche data were available.
F_t = Number of UK publicly quoted companies in the population which entered bankruptcy in year t.
$NFAILS_t$ = Number of companies in the sample which issued their final annual reports in year t, prior to entering bankruptcy.
NGQ_t = Number of companies which received going concern qualifications in year t.

Next, a search was made of Datastream for data on the number of employees, cashflow ratios, profitability ratios and leverage ratios.[10] Data on each company's Standard Industrial Classification (SIC) codes were collected from Extel, because industry sector is likely to be an important determinant of bankruptcy. Data for some of the 1086 companies in the initial sample were unavailable from Datastream and Extel. The final sample comprised 976 companies of which 90 failed over the eight-year period. The frequency of failure in the sample is 1.73% which is approximately equal to the population frequency (Morris, 1997).

3.2. Bankruptcy and audit reporting between 1987–94

Table 1 shows the pattern of bankruptcy and audit reporting over the period 1987–94. Row 1 shows the total number of companies for which audit data were available in the initial sample of 1,086 companies. The number of companies in the final sample (976) exceeds the number of observations in each year due to missing observations.[11] Row 2 shows the number of failing companies in the population. Given the timing of the economic cycle, it is unsurprising that most failures occurred between 1990–92. A comparison of rows 2 and 3 shows that there is an average lag of around a year between the last annual report of a failing company ($FAILS_t$) and its entry into bankruptcy (F_t).[12] Companies which received going-concern qualifications were coded with a 1, whilst those that did not were coded with a zero. Row 4 shows that the number of going-concern qualifications jumped up in 1990 and remained high during the recovery of 1993–94.

3.3. The accuracy of large and small auditors' reports

Panel A of Table 2 shows that both type I and type II error rates are smaller for large audit firms than for small audit firms. The difference in type I error rates was statistically significant at the 10% level, while the difference in type II error rates was not significant. Panel B reports the accuracy rate which is equal to the number of type I and type II errors divided by the total number of reports. For example, large auditors committed 42 type I errors and 58 type II errors in 4511 audit reports; therefore the accuracy rate for large auditors is 97.78% [(4511–42–58)/4511]. The results indicate that the reports of large auditors were significantly more accurate than those of small auditors (at the 1% level). The difference in large and small auditors' accuracy rates was highly significant because *both* type I *and* type II error rates were lower for large auditors.[13]

In panels A and B the bankruptcy horizon was assumed to be a single reporting period—this definition makes sense because of the Auditing Guideline's definition of the 'foreseeable future'. However, the result that large auditors' reports are more accurate is robust to considering alternative bankruptcy horizons. Panel C measures the accuracy of reports when the horizon is two reporting periods (a type I error occurs when a failing company does not receive a qualification in its final or penultimate reports; a type II error occurs when a qualified report is not followed by bankruptcy within two reporting periods). Once again, large auditors' reports were significantly more accurate than small auditors' reports—similar results were found for bankruptcy horizons of more than two periods.

The superior accuracy of large auditors' reports could have occurred because large auditors were more accurate or because it was easier to predict bankruptcy for large auditors' clients. For example, large auditors' clients tend to be large and are unlikely to fail. Therefore, a bankruptcy model was used as a benchmark for evaluating the accuracy of audit reports. If it is easier to predict bankruptcy for large auditors' clients, one should find that the bankruptcy model is more accurate for large auditors' clients. If large auditors are

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[10] These variables are defined in Table 3.

[11] Companies with observations that were missing for reasons other than bankruptcy or take-over were not dropped from the sample because this could cause problems of sample selection bias. There are two reasons why the presence of missing observations is not likely to cause problems. First, there are not very many missing observations—the majority of companies (653) have a complete panel of data covering all eight years. Secondly, when the sample proportion of companies differs from the population proportion, the logit model has consistent coefficient estimates for all variables except the constant (Anderson, 1972). For all models reported in this paper, the results from probit and logit models were found to be very similar and so sample selection bias does not seem to be a problem.

[12] The average lag was in fact 14 months.

[13] When large and small auditors' clients were matched on the basis of size, large auditors' reports were again found to be more accurate than those of small auditors. The data were partitioned into three groups:

Group 1: Company has $\leq$15,000 employees and hires a large auditor (3,971 observations)

Group 2: Company hires a small auditor (1,905 observations)

Group 3: Company has $>$15,000 employees and hires a large auditor (540 observations)

The mean number of employees in Groups 1, 2 and 3 were 2,076, 2,081 and 52,556 respectively. If auditor accuracy depends on company size rather than auditor size, one would expect to find no difference in accuracy rates for Groups 1 and 2 which have similar size companies. In Group 1, the type I and type II error rates (76.36% and 1.48%) were both lower than small auditors' error rates (91.43% and 1.76%). The difference between large and small auditors' type I error rates was statistically significant at the 10% level ($\chi^2 = 3.32^*$), while the difference between type II error rates was not significant. These results are similar to those reported in Table 2, where companies were not sorted into size groups.

Table 2
The correlation between auditor accuracy and auditor size

Panel A — *Type I and Type II error rates of large and small audit firms (Bankruptcy horizon = 1 year)*

	Large audit firms ($AUD_{it}=1$)		Small audit firms ($AUD_{it}=0$)		H_0: equal error rates for large and small audit firms
	$GQ_{it}=0$	$GQ_{it}=1$	$GQ_{it}=0$	$GQ_{it}=1$	
$FAILS_{it}=1$	42	13	32	3	
Type 1 error (%)	76.36		91.43		$\chi2=3.28$*
$FAILS_{it}=0$	4,398	58	1,837	33	
Type II error (%)	1.30		1.76		$\chi^2=1.92$

Panel B — *Overall accuracy of large and small audit firms (bankruptcy horizon = 1 year)*

	Large audit firms ($AUD_{it}=1$)		Small audit firms ($AUD_{it}=0$)		H_0: equal accuracy for large and small audit firms
	Accurate	Inaccurate	Accurate	Inaccurate	
	4,411	100	1,840	65	
Accuracy (%)	97.78		96.59		$\chi^2=7.63$***

Panel C — *Overall accuracy of large and small audit firms (bankruptcy horizon = 2 years)*

	Large audit firms ($AUD_{it}=1$)		Small audit firms ($AUD_{it}=0$)		H_0: equal accuracy for large and small audit firms
	Accurate	Inaccurate	Accurate	Inaccurate	
	4,360	151	1,813	92	
Accuracy (%)	96.65		95.17		$\chi^2=13.00$***

*Significant at the 0.1 level ($\chi^2_{0.1}$ (1 d.f.) = 2.71)
**Significant at the 0.05 level ($\chi^2_{0.05}$ (1 d.f.) = 3.84)
***Significant at the 0.01 level ($\chi^2_{0.01}$ (1 d.f.) = 6.63)
When the bankruptcy horizon is one year, the failure variable is $FAILS_{it}$
$FAILS_{it}=1$ if company i issued its final report in year t prior to entering bankruptcy (90 observations); = 0 otherwise (6,326) observations).
When the bankruptcy horizon is two years, the failure variable is $FAILS_{i(t,t+1)}$
$FAILS_{i(t,t+1)}=1$ if company i issued its final or penultimate report in year t prior to entering bankruptcy (178 observations); = 0 otherwise (6,238 observations)
$GQ_{it}=1$ if company i received a going-concern qualification in year t (107 observations); = 0 otherwise (6,309 observations)
$AUD_{it}=1$ if company was audited by a Big Six auditor in year t; = 0, otherwise

more accurate than small auditors, one should find that large auditors' reports are more accurate, even taking into account differences between large and small auditors' clients. The explanatory variables included in the model are described in the next section.

3.4. Financial distress variables

Data on the main activities of each company were collected because the effects of the economic cycle are likely to differ across industry sectors. Previous research also indicates that cashflow, leverage, profitability and company size are related to financial distress (Altman, 1986). Data on these variables were obtained from Datastream and are defined in Table 3.[14]

The return on capital variable (ROC_{it}) measures profitability whilst capital gearing ($CAPG_{it}$) is a measure of leverage. The gross cashflow (GCF_{it}),

[14] Some studies used total assets rather than number of employees to measure company size. However, assets were found to have lower predictive content than the number of employees.

Table 3
Company size, industry sector, cashflow, leverage and profitability variables

Variable	*Definition*	*Datastream Code*	*Interpretation*
EMP_{it}	Total number of employees	219	Company size
D1	=1 if company i operates in energy or water; =0 otherwise		Industry effects
D5	= 1 if company i operates in construction; =0 otherwise		Industry effects
D8	=1 if company i operates in banking, finance or insurance; =0 otherwise		Industry effects
$DBTN_{it}$	$\frac{\text{(Total sales)} \times 100}{\text{Total debtors}}$	726	Debtor turnover ratio
$CASH_{it}$	$\frac{\text{(Total cash)} \times 100}{\text{Current liabilities}}$	743	Cash ratio
GCF_{it}	$\frac{\text{(Profits earned for ordinary shareholders+Depreciation+Tax equalisation)}}{\text{Capital employed+Current liabilities} - \text{Intangibles}} \times 100$	735	Gross cashflow ratio
$CAPG_{it}$	$\frac{\text{(Preference capital+Subordinated debt+Loan capital+Short-term borrowings)}}{\text{Capital employed+Short-term borrowing} - \text{Intangibles}} \times 100$	731	Capital gearing ratio
ROC_{it}	$\frac{\text{(Total interest charged+Pre-tax profit)}}{\text{Capital employed+Short-term borrowing} - \text{Intangibles}} \times 100$	707	Return on capital ratio

debt-turnover ($DBTN_{it}$) and cash ($CASH_{it}$) ratios measure cashflow. GCF_{it} measures profit-generated cashflow. $DBTN_{it}$ captures the fact that companies are more likely to fail if they are having problems in receiving payments for past sales. $CASH_{it}$ is a measure of short-term liquidity. Other Datastream financial ratios tried were income gearing (leverage measure), credit-turnover, stock-turnover, the working capital ratio and the quick ratio (cashflow measures).[15] These variables were found to have insignificant and/or non-constant effects on bankruptcy and were therefore omitted from the model.

4. Results

Table 4 reports the results for two bankruptcy models. Model 1 is used to evaluate the accuracy of audit reports while model 2 tests the incremental information content of going-concern qualifications. Both models show that cashflow (GCF_{it}) and leverage ($CAPG_{it}$) have non-linear effects on the probability of bankruptcy—these non-linearities were captured by including polynomial variables ($CAPG_{it}^2$, $CAPG_{it}^3$ and $CAPG_{it}^4$ and GCF_{it}^2). Lennox (1999) has shown that a failure to take account of these non-linearities causes heteroscedasticity problems.[16]

The negative coefficients on company size (EMP_{it}) indicate that small companies were more likely to fail. The industry dummies show bankruptcy was more likely for companies operating in the utility ($D1_i$), construction ($D5_i$) or finance ($D8_i$) sectors. The negative coefficients on the debtor-turnover ($DBTN_{it}$) and cash ($CASH_{it}$) ratios show that companies were more likely to fail if payments from past sales were low or if cash reserves fell. The negative coefficients on gross cashflow (GCF_{it})

[15] All these ratios are defined by Datastream, and have the following codes: Income gearing (Datastream code, 732); Creditors' turnover (728); Stock turnover (724); Working capital ratio (741); and the Quick ratio (742).

[16] Langrange Multiplier tests for omitted variable bias and heteroscedasticity show that the bankruptcy model does not suffer from mis-specification problems. Lennox (1999) also tested the model using separate estimation (1987–90) and hold-out (1991–94) samples, and found that the coefficient estimates are stable over the period 1987–94. Standard errors were calculated using the Huber bootstrapping technique which gives consistent standard errors under very weak assumptions; for example, the formula does not require the standard assumptions of no serial correlation or homoscedasticity (Huber, 1967). Huber's formula is a canned part of the STATA statistical package and can be used in conjunction with the probit command.

Table 4
Bankruptcy models
(z-statistics in parentheses)

Control variables	*Model 1*	*Model 2*
EMP_{it}	−0.379e−04	−0.110e−05
	(−2.581)***	(−0.064)
AUD_{it}* EMP_{it}		−0.606e−04
		(−2.634)***
$D1_t$	0.432	0.439
	(1.810)*	(1.869)*
$D5_t$	0.328	0.368
	(2.506)**	(2.740)***
$D8_t$	0.398	0.406
	(3.754)***	(3.790)***
$DBTN_{it}$	−0.200e−03	−0.186e−03
	(−2.010)**	(−1.837)*
$CASH_{it}$	−0.472e−02	−0.435
	(−2.325)**	(−2.087)**
GCF_{it}	−0.215e−03	−0.902e−02
	(−2.340)**	(−1.334)
GCF_{it}^2	−0.205e−03	−0.191e−03
	(−2.072)**	(−1.764)*
$CAPG_{it}$	-0.245e−03	0.254e−03
	(7.698)***	(8.046)***
$CAPG_{it}^2$	−0.845e−08	−0.877e−08
	(−5.344)***	(−5.435)***
$CAPG_{it}^3$	0.587e−13	0.613e−13
	(4.802)***	(4.914)***
$CAPG_{it}^4$	−0.112e−18	−0.118e−18
	(−4.491)***	(−4.630)***
ROC_{it}	−0.323e−04	−0.414e−04
	(−1.771)	(−1.559)
AUD_{it}		−0.150
		(−1.320)
CONSTANT	−2.822	−2.806
	(−19.519)***	(−18.462)***
Experimental Variables		
GQ_{it}		−0.398
		(−1.135)
AUD_{it}* GQ_{it}		0.777
		(1.948)*
Number of Observations	6416	6416
Number of companies	976	976

***Significant at the 0.01 level. **Significant at the 0.05 level. *Significant at the 0.1 level.
All variables defined in Tables 2 and 3.

also show that a company was more likely to go bankrupt when profit-generated cashflow was low.

The positive coefficient on capital gearing ($CAPG_{it}$) shows that highly-levered companies were more likely to fail. While the polynomial terms $CAPG_{it}^2$ and $CAPG_{it}^4$ have negative coefficients, the effect of leverage on bankruptcy was monotonically positive for values of $CAPG_{it}$ lying within two standard deviations of its mean. Finally, the negative coefficient on profitability (ROC_{it}) implies that companies with low (or negative) profits were more likely to fail.

Table 5 compares model 1's predictive accuracy for large and small auditors' clients to investigate whether the positive correlation between auditor accuracy and auditor size is due to client-specific or auditor-specific factors. Panel A reports the type I and type II error rates for auditors and model 1 (auditors' error rates are the same as Panel A of Table 2). The cut-off probabilities (P*)

Table 5
Predictive accuracy of audit reports and model 1 for large and small auditors' clients

Panel A

Type I and Type II error rates of large and small audit firms

	Large audit firms ($AUD_{it}=1$)		Small audit firms ($AUD_{it}=0$)		H_0: equal error rates for large and small audit firms
	$GQ_{it}=0$	$GQ_{it}=1$	$GQ_{it}=0$	$GQ_{it}=1$	
$FAILS_{it}=1$	42	13	32	3	
Type I error (%)	76.36		91.43		$\chi^2=3.28$*
$FAILS_{it}=0$	4,398	58	1,837	33	
Type II error (%)	1.30		1.76		$\chi^2=1.92$

Type I and Type II error rates of model 1

	Large audit firms' clients ($AUD_{it}=1$)		Small audit firms' clients ($AUD_{it}=0$)		H_0: equal error rates for large and small audit firms' clients
Cut-off (P*)	0.187		0.151		
	SURVIVE	FAIL	SURVIVE	FAIL	
$FAILS_{it}=1$	40	15	27	8	
Type I error (%)	72.73		77.14		$\chi^2=0.22$
$FAILS_{it}=0$	4,400	56	1,842	28	
Type II error (%)	1.26		1.50		$\chi^2=0.58$

Panel B

Overall accuracy of large and small audit firms

	Large audit firms ($AUD_{it}=1$)		Small audit firms ($AUD_{it}=0$)		H_0: equal accuracy for large and small audit firms
	Accurate	Inaccurate	Accurate	Inaccurate	
	4411	100	1840	65	
Accuracy (%)	97.78		96.59		
					$\chi^2=7.63$***

Overall accuracy of model 1

	Large audit firms' clients ($AUD_{it}=1$)		Small audit firms' clients ($AUD_{it}=0$)		H_0: equal accuracy for large and small audit firms' clients
Cut-off (P*)	0.187		0.151		
	Accurate	Inaccurate	Accurate	Inaccurate	
	4,415	96	1,850	55	
Accuracy (%)	97.87		97.11		$\chi^2=3.36$*

*Significant at the 0.1 level ($\chi^2_{0.1}$ (1 d.f.) = 2.71).
**Significant at the 0.05 level ($\chi^2_{0.05}$ (1 d.f.) = 3.84)
***Significant at the 0.01 level ($\chi^2_{0.01}$ (1 d.f.) = 6.63)
$FAILS_{it}$ = 1 if company i issued its final report in year t prior to entering bankruptcy (90 observations); = 0 otherwise (6,326) observations).
GQ_{it} = 1 if company i received a going-concern qualification in year t (107 observations); = 0 otherwise (6309 observations).

for model 1 were chosen such that the number of predicted bankruptcies was equal to the number of going-concern qualifications. Since large auditors gave 71 (13+58) going-concern qualifications, the cut-off probability for large auditors' clients was 0.187, as this resulted in 71 predictions of failure by model 1. Similarly, small auditors gave 36 going-concern qualifications and the cut-off probability for small auditors' clients was 0.151. This rule for choosing P* ensured that model 1 reflected the degree of auditor conservatism. Choosing a lower (higher) P* would increase (reduce) the number of predicted failures. Since most companies are non-failing, choosing a lower (higher) P* would artificially reduce (increase) model 1's accuracy compared to audit reports.

There are three things to note from Table 5. First, model 1 was more accurate than both large and small auditors' reports. Model 1's type I and type II error rates for large auditors' clients were 72.73% and 1.26%, while the error rates of large auditors were 76.36% and 1.30% respectively. Model 1's type I and II error rates for small auditors' clients were 77.14% and 1.50%, while the error rates of small auditors were 91.43% and 1.76% respectively. This is consistent with previous research showing that audit reports are poor indicators of financial distress compared to bankruptcy models (Koh, 1991).

Secondly, the bankruptcy model was more accurate for large auditors' clients than for small auditors' clients. Model 1's type I and type II error rates were 72.73% and 1.26% for large auditors' clients, but 77.14% and 1.50% for small auditors' clients. This indicates that it is easier to predict bankruptcy for large auditors' clients than small auditors' clients. This demonstrates the importance of controlling for differences in client characteristics when comparing the accuracy of large and small auditors.

Finally, Panel B shows that large auditors were significantly more accurate than small auditors, even after controlling for client characteristics. The difference in reporting accuracy between large and small auditors was highly significant (at the 1% level), while the difference in model 1's accuracy between large and small auditors' clients was less significant (at the 10% level). While model 1 classified 8 (0.18%) companies more accurately than large auditors, it classified 20 (1.05%) companies more accurately than small auditors. Had model 1's superior accuracy been the same for both large and small auditors' clients, one would have expected these numbers to be 19.7 and 8.3 respectively (rather than 8 and 20). One can reject the null hypothesis that model 1 is equally more accurate for large and small auditors' clients at the 5% level ($\chi^2=6.40^{**}$). Since model 1's superior accuracy is significantly greater for small auditors' clients, the evidence indicates that large auditors were significantly more accurate.

Model 2 in Table 4 tests whether audit reports signal useful incremental information about the probability of bankruptcy by including going-concern qualifications (GQ_{it}) as a predictor. To investigate whether the information content of audit reports is related to auditor size, GQ_{it} is interacted with an auditor size dummy (AUD_{it}) which takes a value of one if the auditor belonged to the Big Six.

Prior to estimating model 2, model 1 was re-estimated for large and small auditors' clients to investigate any differences in coefficient estimates. The relationship between client size (EMP_{it}) and bankruptcy was found to be greater for large auditors' clients than small auditors' clients. Therefore, a variable capturing the interaction between client and auditor size ($AUD_{it}*EMP_{it}$) is included in model 2. The insignificant negative coefficient on going-concern qualifications (GQ_{it}) shows that audit opinions did not signal useful incremental information about the probability of bankruptcy. The positive coefficient on the interaction variable ($AUD*GQ_{it}$) is significant at the 10% level (but not the 5% level). Although large auditors' going-concern qualifications may have signalled useful information about the probability of bankruptcy, the statistical significance was not high. The standard errors for the coefficients on GQ_{it} and $AUD_{it}*GQ_{it}$ were 0.351 and 0.399, respectively. Thus, the difference between the coefficients on GQ_{it} (-0.398) and on $AUD_{it}*GQ_{it}$ (0.777) were statistically significant at the 5% level—one can reject the null hypothesis that large and small auditors' going-concern qualifications had equal information content.

5. Conclusion

Large auditors are significantly more likely to give going-concern qualifications to failing companies and clean opinions to non-failing companies. Results from a bankruptcy model suggest that this is partly because it is easier to predict bankruptcy for large auditors' clients than for small auditors' clients. However, even after controlling for differences between large and small auditors' clients, large auditors give significantly more accurate reports compared to small auditors. The incremental information content of audit reports was tested by including going-concern qualifications in the bankruptcy model. While the statistical significance of large auditors' reports was weak, they were significantly better predictors of bankruptcy compared to small auditors' reports. A caveat to the methodology of this and previous papers is that going-concern qualifications are not equivalent to bankruptcy predictions by auditors—thus, the correlation between audit opinions and bankruptcy outcomes may not fully capture differences in accuracy.

Overall, the results are consistent with the reputation and deep pockets theories, which predict that large auditors have more incentive to exert effort in order to avoid issuing inaccurate reports. An alternative explanation, unrelated to effort or reporting incentives, is that large auditors are more competent at obtaining or interpreting audit evidence. For example, large audit firms may have more staff with client-specific knowledge, they may be more experienced in auditing large quoted companies, or they may engage in greater industry specialisation. Future research therefore needs to investigate whether the superior accuracy of large auditors is due to their deeper pockets, reputation effects or greater competence.

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