The Impact of Filing Micro-Entity Accounts and the Disclosure of Reporting Accountants on Credit Scores: An Exploratory Study

Abstract

There is a dearth of evidence regarding the potential costs incurred by small private companies that opt to publish only an unaudited abbreviated balance sheet. This paper provides new evidence regarding whether UK companies that publish reduced balance sheet information in micro-entity annual accounts are allocated lower credit scores by a credit rating agency. Recently, for the smallest companies, a new exemption category for 'micro-entities' was introduced. Qualifying companies may elect to file even less unaudited balance sheet information than their small company counterparts. Consistent with the conjecture that publishing micro accounts conveys a negative signal to the credit scorer, there is systematic evidence that micro-entities are assigned worse credit scores. This result is robust to the employment of statistical methods that account for observed and unobserved bias. Based on both assurance and signalling tenets, the second novel conjecture examined in this study, is that companies which disclose their annual accounts are prepared by an accountancy firm (reporting accountant) will attract higher credit scores. Contrary to extant research which reports that companies that opt for voluntary audits receive higher credit scores, there is no evidence that the credit scorer rewards companies whose accounts bear the imprimatur of a reporting accountant.

Keywords: micro companies; credit scores; abbreviated accounts; reporting accountants; observed and unobserved bias

The Impact of Filing Micro-Entity Accounts and the Disclosure of Reporting Accountants on Credit Scores: An Exploratory Study

1. Introduction

This empirical paper presents new evidence on whether UK private companies which publish reduced balance sheet information in micro-entity annual accounts are allocated lower credit scores by a credit rating agency (hereafter referred to as the credit scorer). The paper also provides novel evidence on whether companies whose annual statutory accounts disclose they are prepared by an accountancy firm (hereafter referred to as a reporting accountant) obtain higher credit scores. As demonstrated in the next section, UK small companies rely heavily on debt financing, so credit ratings are important in terms of their potential influence on the availability and cost of debt. The study is exploratory in that, to the author's knowledge, extant archival studies do not investigate the relationship between corporate outcomes and reduced financial disclosure under the small/micro company reporting regimes - nor the disclosure that companies have a reporting accountant. Hence, as well as being of academic interest, it is hoped that the results of this study will prove informative for policy makers/regulators and small company accountants.

Despite its economic importance, and the perennial intervention of policy-makers, the small company sector has received relatively little (but growing) attention from accounting researchers (see Kitching *et al*. 2011, Collis 2012, Kitching, Kašperová and Collis 2015). A recent ICAEW report (Singleton-Green 2015), which contains a review of extant SME survey and archival accounting research, stresses (p. 9) that 'Valuable though this research is, it tells us remarkably little about the effects of regulating or deregulating SME financial reporting'. Though providing important evidence and insights, prior archival accounting research concentrates on the minority of small companies which voluntarily publish full accounts and then examines the association between voluntarily audits and various corporate outcomes, including the cost of debt and credit scores (Singleton-Green 2015). In contrast, and given the diminishing proportion of companies opting for voluntary audits, this study focuses on the vast majority of small UK companies which publish unaudited accounts, containing only an abbreviated balance sheet.

All UK companies must file annual accounts at Companies House (CH, the UK repository for company filings) where they are then available for public inspection. However, in the UK (and the EU) small private companies are exempt from the requirements to publish full audited annual accounts (as their larger counterparts must do) on the grounds of lifting the administrative burden on the small company sector. The company size criteria for claiming these exemptions have been relaxed through time (Collis 2012). Clatworthy and Peel (2013) report that a minority (17.9%) of small UK companies with year ends in 2009/10 voluntarily filed full or audited accounts, with the typical small company opting to file only an unaudited abbreviated balance sheet (hereafter referred to as small company accounts). Following an EU directive aimed at reducing the administrative burden still further for the smallest companies (see DBIS 2013, Kitching et al. 2015), a new exempt category, 'micro-entities', was recently introduced. Small UK private companies which meet specific (smaller) size criteria need only file an unaudited abbreviated balance sheet (hereafter referred to as micro company accounts), which contains even less financial information than small company accounts.

Intuitively, and as explicitly stated (DBIS 2013, p. 5), the motivation underpinning these exemptions is that, given the lack of divorce between ownership and control, audits/full accounts are of less import, since most small companies do not suffer substantive agency problems. However, as discussed below, in such a reporting environment, increased voluntary accounting disclosures may act as a signal (see e.g. Toms 2002, Watson, Shrives and Marston 2002) to outsiders (including credit rating agencies) that the company is of higher quality (lower risk). In line with this, the first conjecture examined in the current study is that, relative to small companies publishing abbreviated accounts, those which opt to file micro-company accounts, which divulge even less information, will be assigned worse credit scores. In this context, and with reference to the new micro-entities' exemption, Collis (2012, p. 442) comments that 'there is a paucity of up-to-date research on the benefits that might be lost', and that 'A further limitation is that previous impact assessment studies on raising the thresholds in the UK have necessarily focused on predicted behaviour rather than the actual choices made' (p. 443). The current study provides new archival evidence regarding the filing choice exercised.

Extant archival research finds that voluntary audits are associated with higher credit scores (Dedman and Kausar 2012, Lennox and Pittman 2011). This is consistent with the credit scorer viewing audited accounts as being of higher quality (the company being of lower risk) in accord with assurance/signalling principles.

Similarly, small and micro companies in the current study may voluntarily appoint an accountancy firm to compile their annual accounts. On the same tenets (assurance/signalling) obtaining to voluntary audits, the second conjecture examined in this paper is that companies whose annual accounts contain the imprimatur of an accountancy firm (reporting accountant) will be rewarded with higher credit scores.

The remainder of this paper is organised as follows: Section 2 presents background information and provides motivation for the conjectures examined in the empirical study. Section 3 describes the research design and data, as well as reporting descriptive statistics. Section 4 presents the results of the empirical study, before the paper concludes in Section 5.

2. Background and study conjectures

Based on survey evidence from 4,500 SME businesses (employees ≤ 249), BDRC provides detailed information on financing in the UK SME sector. For 2016, it reports (BDRC 2017, p.11 and p. 58) that only 63% of SMEs used any form of external finance (including debt finance, trade credit and 'injections of personal funds'), with 38% receiving 'core' external debt finance (bank overdrafts, loans/commercial mortgages and credit cards) and with 15% of SMEs relying solely on trade credit (p. 82). Risk ratings show (p. 24) that, as with the current study, larger businesses are associated with better risk ratings. In addition, SMEs with superior risk ratings were more likely to receive trade credit (p. 74). However, the information provided by BDRC does not differentiate companies from other forms of business ownership. At the start of 2016, official government estimates indicate that there were about 5.5 million UK businesses, of which around 60% were sole proprietorships, 8% were ordinary partnerships and 32% were actively trading companies (DBEI 2016a).

Table 1 about here

The use of debt finance by small UK companies appears to be much higher than that reported for all businesses in the BRDC surveys. In particular, Clatworthy and Peel (2013, p.11) express 'surprise' that the median gearing ratio (as defined in this study) of all small UK independent private companies (n= 1,067,577) with year ends falling in 2009/10 amounted to 0.78, with 41.4% (21.8%) of small companies exhibiting negative working capital (negative equity). Contemporary evidence is consistent with these findings. Table 1 reports gearing statistics for sample of 100,000 UK companies randomly selected from all (n=1,101,600) UK private independent (not held as a subsidiary) live companies (not failed/dormant) available on the FAME database (see below). Data was collected in September 2017 and relates to companies with year ends in the corporate fiscal year to March 2017. Statistics are reported for size categories based on total assets (TA), including those corresponding to the TA limits of £316k (£3.26m) which, as discussed below, are applicable to the micro (small) company reporting regimes. As shown in the table, because mean gearing levels (GEAR) - defined as the ratio of total liabilities to TA - are skewed heavily upwards for smaller companies, as well as median GEAR values, mean winsorised gearing ratios (WINGEAR) are presented where GEAR values $\geq$ 3 are winsorised at a value of 3.

In general, and consistent with the findings of Peel and Clatworthy (2013), Table 1 reveals that small private companies exhibit high gearing levels. Compared to the largest private companies (TA > £3.26m), with median (mean WINGEAR) gearing values of 0.590 (0.627), those for the smallest ones (TA $\leq$ £100,000) are substantially higher at 0.852 (0.942) respectively. Because the median is not influenced by outliers, it is informative that, for all UK private companies, the median gearing ratio of 0.768 emphasises the important role of debt financing in this market. As reported in Table 1, 2.2% of all companies have no debt financing (GEAR = 0), with 18.5% exhibiting negative equity. The proportions of companies with zero gearing (negative equity) are inversely related to company size (TA), with values of 0.7% (6.3%) for the largest companies, rising to 3.0% (22.5%) for the smallest ones. In summary, the high use of debt finance by small private independent companies suggests that credit scores may be important, to the extent that they influence the cost and availability of external finance, including trade credit and potential equity investors.

CH classifies (as does the FAME database used in this study) companies filing micro accounts as 'micro-entity accounts' and small companies filing only an unaudited abbreviated balance sheet as 'total exemption small'. Micro companies may voluntarily file an abbreviated profit and loss account and/or may voluntarily appoint an auditor. As explained below, such companies are excluded from the analysis, so that only micro companies filing an unaudited abbreviated balance sheet remain.

At the time of this study[1], private independent companies were classified as small, and could elect to

[1] For accounting periods on or after 01/01/2016, the size limits for small company filing exemptions for sales (total assets) were increased to £10.2 million (£5.1 million). In addition, for accounting periods on or after 01/01/2016, small (but not micro) companies are subject to a new reporting regime. As described by Price Bailey (PB 2017), though the regulations

file only an unaudited abbreviated balance sheet, if they met at least two of the following criteria: sales ≤ £6.5m, total assets ≤ £3.26m and number of employees ≤ 50. Recently, a new UK statutory filing category aimed at the smallest (micro) companies was introduced for account year ends falling after 30 September 2013. Companies are classified as micro-entities if they meet at least two of the following criteria: sales ≤ £632,000, total assets ≤ £316,000 and number of employees ≤ 10. Micro companies need only file an abbreviated balance sheet which contains less financial information than those companies classified as small. Hence micro companies can choose to opt out of the small company reporting regime and file annual accounts which contain less balance sheet information[2]. As mentioned above, the (then) government's rationale for the new micro reporting category is that it 'eases burdens on the very smallest of companies' (DBIS 2013, p. 5).

However, based on survey evidence, it did acknowledge (DBIS 2013, p.11) that 'clearly, the owners and directors of micro-entities will need to assess the possible effect of reduced disclosures on their company and decide which form of financial statement … best meets their company's needs'. Note that, other than with regard to increased privacy (less information available to competitors), it is not obvious how the costs (financial or otherwise) are reduced when companies are permitted to file abbreviated accounts. In fact, given full accounts must be prepared to derive abbreviated ones, and that (in the UK) information from full accounts is required for tax purposes, the cost of filing abridged ones is marginally higher (see Dedman and Lennox 2009, p. 211, Collis 2012, p. 446).

Table 2 about here

Table 2 shows the difference in disclosure requirements for small and micro companies filing abbreviated annual accounts, together with the legislation governing the disclosures. It shows that, whereas small companies are required to show the elements of current and fixed assets, micro ones need only reveal the totals. The other difference is with regard to shareholders' funds. Unlike micro companies, small ones must report its constituents. As shown, both micro and small companies are not required to disclose the components of current and long term liabilities in the balance sheet or in notes to the balance sheet; nor are they required to

are more complex, small companies need only file an abridged balance sheet, the contents of which are similar to those obtaining to abbreviated accounts (as studied in this paper) under the former small company reporting regime.

[2] Certain financial service companies - such as those providing insurance, banking or investment services - are not permitted to file micro or small company abbreviated accounts and are therefore naturally excluded from the current study.

disclose the number of their employees. In this context, although Dedman and Kausar (2012) employ (as does the current study) a variable denoting a company has negative equity (shareholders' funds), neither Lennox and Pittman (2011), nor Dedman and Kausar (2012), incorporate variables based on the individual elements of current assets or shareholders' funds when examining the relationship between voluntary audits and credit scores on the FAME database. In any event, endogeneity concerns are addressed using appropriate econometric techniques in the empirical analysis below.

Regarding the preceding discussion, signalling theory (e.g. Spence 1973,Toms 2002) suggests that companies may make voluntary disclosures to signal to outsiders that they are of higher quality (lower risk). The credibility of this signal may be enhanced if the company incurs disclosure costs (Melumad and Thoman 1990). Such corporate costs include the loss of confidentiality (from competitors) associated with fuller disclosure. Given this, the first conjecture of this study is that, relative to small companies filing abbreviated accounts, those which exercise their option to file micro ones will be penalised by the credit scorer. This is hypothesised to occur because the credit scorer is aware that the typical small company files abbreviated accounts under the small company regime. By opting out of this regime, and divulging even less balance sheet information, the filing of micro accounts is postulated to convey a negative signal to the credit scorer that companies who do so are of lower quality (higher risk). In addition, by electing to be known publicly as a micro-entity may *per se* be viewed negatively by the credit scorer with reference to corporate strategic orientation/ambition/growth prospects. This leads to the first hypothesis[3]:

H1*: Companies filing micro-entity annual accounts will receive lower credit scores.*

Despite the benefits which have been found to accrue to small companies which voluntarily appoint auditors (Singleton-Green 2015), the proportion doing so has shrunk through time (Collis 2012, Clatworthy and Peel 2013). As Dedman and Kausar (2012, p.146) stress, 'by allowing progressive size-based audit exemptions

[3] Although not affecting the current study, for accounting periods beginning on or after 01/01/2016, new UK financial reporting standards (FRS) were introduced. Companies filing abbreviated accounts under the micro regime must adopt FRS 105; whereas those filing accounts under the small company regime must apply Section 1A of FRS 102, which is of a higher standard (see FRC 2015a, p.12, FRC 2015b, p. 4). Small companies (including those which qualify as micro-entities) may choose to voluntarily file full accounts which are subject to higher reporting standards. In terms of potential future research, the higher standard (quality) of reporting under Section 1A of FRS 102, as compared with that of FRS 105, would strengthen *H1*, in that the credit scorer may upgrade credit scores to reflect superior reporting standards.

for private firms, the UK has been steadily moving towards a largely audit-exempt private sector'. This emphasises the increasing import of the market for reporting accountants in the small company sector (FRC 2006). Clatworthy and Peel (2013) show that the UK small company reporting environment was dominated by companies restricting their accounts to include only an unaudited abbreviated balance sheet. Of all small UK independent private companies with year ends in 2009/10 (n=1,067,577), they report (p.11) that 84.7% filed small company unaudited abbreviated accounts. Only 3.2% of small companies had appointed an auditor. Also, although (generally) there is no divorce between ownership and control in private companies, the Financial Reporting Council (FRC 2006, p. 37) reported that at least 67% of SME companies check potential customer credit worthiness before issuing credit; and 'accountants told us that their clients may use a credit rating agency for this purpose'.

As commented by Singleton-Green (2015, p. 26), 'Audits should lead to higher financial reporting quality, which should ultimately lead to other benefits, in particular for SMEs a lower cost of borrowing.' In reviewing the literature, Singleton-Green (2015) documents that voluntary audits are associated with a lower cost, and the increased availability, of debt finance. Importantly, in examining UK small companies on the FAME database which voluntarily filed full accounts, studies by Dedman and Kausar (2012) and Lennox and Pittman (2011) report that, consistent with the value of audit assurance (credibility of financial reporting), voluntary audits are associated with higher credit scores. Lennox and Pittman (2011) also find that companies which were subject to mandatory audits, but which retained their auditors following a relaxation in mandatory auditee size requirements, were rewarded with credit score upgrades. They postulate this occurs 'because their decision to remain audited conveys an incrementally positive signal about their credit risk' (p. 1657). Note that signalling is credible in that it is costly (audit fees); so that 'the decision to bear the cost of an audit enables the low-risk types to better differentiate themselves from the high-risk types' (Lennox and Pittman 2011, p. 1660).

The directors of small or micro audit exempt companies are not required to use an accountant to prepare statutory annual accounts (or for any other purpose). Under the company acts, it is the directors who are responsible for keeping adequate accounting records, for producing and filing statutory accounts in the appropriate regulatory format and for signing (approving) the accounts to the effect that they provide a true and fair view[4]. However, companies may voluntarily appoint an accountancy firm (reporting accountant) to prepare their statutory annual accounts and to state (publish) the accountancy firm's details therein. Where this is the case, UK professional accounting bodies recommend that the annual accounts should include an accountant's report (see FRC 2006, ICAEW 2017, ACCA 2017). For instance, the Association of Chartered Certified Accountants (ACCA 2017, p.1) 'recommends that the ACCA accounts preparation report should be given where the practitioner's or firm's name is associated in any way with the financial statements which have been prepared by them'. As explained further below, for general interest, and to inform potential future research, Table 3 contains a reproduction of a typical accountant's report[5] included in the annual accounts of a company sampled for the current study. As shown, the report sets out the directors' duties, the basis on which the accounts are prepared and the exclusion of liability beyond the company and its directors.

Table 3 about here

With regard to private companies, Clatworthy and Peel (2013, p. 3) state that outsiders rely on the information in annual accounts for debt contracting and supplying trade credit[6]; and that 'the accuracy of the information filed by private companies is potentially important to these users and to credit rating agencies that are a primary source of information to lenders'. On the same tenets (assurance/signalling) obtaining to voluntary audits discussed previously, the second conjecture of this study is that companies whose financial statements disclose they have voluntary appointed a reporting accountant will receive higher credit scores.

As discussed above, it is expected that the credit scorer will reward companies based on the assurance tenet (an accountant endorsing the integrity of a company's annual accounts) and/or based on the positive signal[7] (as per Lennox and Pittman 2011) conveyed to the credit scorer when the annual accounts bear the

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[4] However, CH does advise small/micro companies that 'you may wish to consult a professional accountant before you prepare accounts' (CH 2015, p. 20).

[5] The FAME database used in this study only includes a variable containing the accountants name and not whether the accounts include an accountant's report. It is therefore highly unlikely that the FAME credit scorer uses the latter in determining scores (see also footnote 24).

[6] In this context, Kitching *et al*. (2011, p. 28) state that around '935,000 abbreviated accounts are downloaded annually' from CH by users. Survey research of UK SMEs (Collis 2008, p. 35) reports that directors considered the main users of their annual accounts were suppliers and other trade creditors (64%), credit rating agencies (62%), competitors (57%) and bank and other lenders (46%).

[7] Though this study cannot disentangle assurance and signalling influences, as do Lennox and Pittman (2011) for voluntary audits, both are postulated to be positively associated with credit scores. Note also with regard to costly signalling (Dharan 1992, Lennox and Pittman 2011), that the cost of hiring an auditor is higher than that for a reporting accountant.

imprimatur of an accountancy firm. Though the signalling/assurance value associated with a reporting accounting is expected to be less than that of a voluntary audit[8] (see Table 3), it is predicted that companies with a reporting accountant will be associated with higher credit scores; given that in the absence of a reporting accountant, the credit scorer is unaware who prepared the annual accounts.

H2*: Companies whose annual accounts disclose they have appointed a reporting accountant will receive higher credit scores.*

The focus of this study in terms of research design/empirical analysis is companies in their start-up phase. The influential study of Berger and Udell (1998) emphasises that small start-up firms are the most informationally opaque, in that they lack a track record and so 'may have difficulty building reputations to signal high quality … to overcome informational opacity' (p.16). When investigating the financing of Belgian manufacturing corporate start-ups, Huyghebaert and Van de Gucht (2007) stress that 'At the start-up stage, outside financiers have no historical data about the firm, which leads to a higher asymmetry in information compared to established firms' (p.102); and find that 'entrepreneurs who provide a credible quality signal … have a larger fraction of bank debt' (p.129). Similar points obtain in the literature relating to initial public offerings (IPOs), when information asymmetries are pronounced (e.g. Holland and Horton 1993, Firth and Liau-Tan 1998). In examining UK IPOs in the (then) Unlisted Securities Market, Holland and Horton (1993, p.19) state that in 'the context of information asymmetry … the status of the professional advisers employed by the company is used as a signal of the quality of the IPO.' They find evidence in support of this conjecture, in that the appointment of 'higher quality' (larger) auditors is associated with smaller initial share price discounts. In accord with this literature, any signalling/assurance value associated with filing choice (*H1*) and reporting accountants (*H2*) is likely to be especially valuable to the credit scorer (and hence empirically detectable) when assigning credit scores to young, informationally opaque small companies.

3. Research design, data and descriptive statistics

3.1 *Data and sample design*

All data for this study were downloaded from the FAME internet database, which contains information for all

[8] Employing a cross-sectional regression model (as in the current study), Dedman and Kausar (2012) report that voluntary audits are associated with an 11.9 increase in FAME credit scores. Hence, the predicted increase in credit scores associated with the disclosure of a reporting accountant would be expected to be less than this.

UK companies, in January 2016. The database is prepared for Bureau Van Dijk by Jordans Limited (see below). Companies were initially selected if they were 'live' (not failed/dormant[9]), private, independent (not held as a subsidiary) and had account year ends falling in the corporate fiscal year to March 2015 (the latest available on FAME). A total of 35,983 private independent companies meeting these requirements had filed micro-entity accounts[10], with 822,087 having filed small abbreviated unaudited ones, of which 712,631 (86.7%) had total assets ≤ £316,000. As described below, to ensure broad initial size homogeneity, only micro/small companies with total assets ≤ £316,000 (the upper qualifying total assets limit for a micro-entity) are included in the estimation sample.

The original research objective of this study was to examine only company start-ups which had filed their first set of accounts, since (as discussed above) start-ups are the most informationally opaque companies, information asymmetries are especially marked - and hence their initial credit scores, and the signalling/ assurance value associated with filing micro accounts and the disclosure of reporting accountants, may be of particular import (Berger and Udell 1998). However, on downloading some initial data, it became clear that no credit scores were allocated to start-ups whose accounts disclosed negative equity[11] (total assets < total liabilities). In consequence, this data was abandoned since empirical models and inferences would be restricted (atypical). Rather, data was collected for micro and small companies which had filed their second and fifth set of accounts. These companies are in the early stage of their life cycle, and as mentioned previously, their allocated credit scores may be especially important with regard to raising finance.

In addition, as argued above, evidence in support of *H1* or *H2* is more likely to be detected when information asymmetries (for young companies) are pervasive; and hence when the value (to the credit scorer) of signalling/assurance is especially pronounced. Companies that had filed their fifth set of accounts were selected with a view to examining whether more established companies (though still in their start-up phase) are

[9] Unsurprisingly, credit scores are not allocated to companies which fail.

[10] Note that, although the number filing micro accounts is comparatively small, it had increased substantially to 81,917 when the FAME database was examined a year later (with the same sampling criteria, but for micro companies with year ends falling in the fiscal year to March 2016). This may indicate an increasing awareness amongst directors of the relatively new micro-entity filing option.

[11] This strongly suggests that negative equity may be an important variable in the credit scoring model (below). Note also that on checking data on FAME one year later (fiscal year to March 2016), start-up companies with negative equity were still not being awarded credit scores. Hence, exclusion of the latter by the credit scorer is a permanent feature.

rewarded with higher credit scores (Dedman and Kausar 2012). Furthermore, restricting the sample to companies filing their second/fifth set of accounts ensures a reasonable degree of uniformity when estimating regression/matching models[12], whilst facilitating an examination (below) of the robustness of the empirical findings when models are estimated separately for companies which had filed their second/fifth set of accounts. Specifically, companies which had filed their second or fifth set of accounts are still in their start-up phase, but the latter are more mature (having filed an additional three sets of accounts), providing a reasonable basis to examine whether the findings relating to the experimental variables persist across the two subsamples.

Data for all micro companies on FAME (n=6,996) who had filed either their second (n= 4,965) or their fifth set of accounts (n=2,031) was downloaded. Using FAME random sampling software, data was also collected for a random sample of 4,000 small companies with total assets ≤ £316,000. These comprise a random of 2,000 small companies who had filed their second set of accounts, together with a random sample of 2,000 companies which had submitted their fifth set of accounts (see Section 4.5 for a discussion of the limitations of this study). However, as discussed below, in addition to the primary samples, basic information (variables) for all 35,983 micro companies, together with that for a random sample of 40,000 small companies drawn from the available 822,087 mentioned above, was also downloaded from FAME. As reported in Table 6 (below), statistics indicate that credit scores differences between micro and small companies are persistent across these extended samples.

Table 4 about here

Table 4 shows how the final estimation sample is constructed. To ensure broad size homogeneity, micro companies with total assets > £316,000 are excluded (n=135). Note that, as described above, the initial sample of small companies was restricted to those with total assets ≤ £316,000 with this in mind. In addition, the application of this size filter ensures that most (if not all) of the sampled small companies could have opted to file micro accounts. This is because even if some have sales above the micro regulatory limit (£632,000), they are highly likely to have 10 or fewer employees. Specifically, official data estimates (DBEI 2016b) reveal

[12] A further reason is that FAME data discs are no longer available. The discs facilitated the downloading of unlimited data. However, based on the number of companies/variables, the FAME internet database imposed a limit on the number of companies/variables that could be downloaded; requiring several file downloads. Hence, focusing on all micro companies which had filed their second or fifth set of accounts, together with 4,000 small companies which had similarly filed their second or fifth set of accounts, appeared to be a reasonable research approach.

that 87.9% of all UK companies had 9 or fewer employees (the definition of a micro company used in UK official statistics) at the start of 2016. As the table reveals, a further 3(4) micro (small) companies which had auditors (a negative gearing ratio) are also excluded[13]; and 59(76) had not been allocated credit scores[14].

A total of 228 micro companies are omitted because they voluntarily filed a profit and loss statement, with a further 8 small companies excluded because they disclosed profit and loss data - and had therefore been incorrectly classified by CH as 'total exemption small' (see above). Hence, all small and micro companies in the final sample had filed only an unaudited abbreviated balance sheet at CH. Lastly, a relatively large number of micro (1,069) and small (1,381) companies are excluded because they have no (zero) current liabilities; and hence the current ratio (below) could not be computed. However, as a robustness test, results are reported where these companies are included in the estimation sample via a dummy (binary) variable approach.

3.2 *Model specification and variables*

Variable labels and definitions are reported in Table 5. The full model specification is:

Credit score (CREDSCR) = $\alpha_0 + \beta_1$MICRO + β_2REPACC + β_3SIZE + β_4GEAR + β_5CACL + β_6NEGEQ +β_7NEGWC + β_8FATA + β_9COURT + β_{10}DEFLT + β_{11}CHARGE + β_{12}DIVERS + β_{13}DUM5 + β_{14}LNSHR +β_{15}LNDIR + β_{16}SHRDIR + β_{17}IND + ε where IND represents a vector of industry dummy variables.

FAME credit scores are developed and maintained by CRIF Decision Solutions Limited in conjunction with Jordans Limited, who also prepare FAME data. As well as the credit scores being available to subscribers to FAME (such as banks), they are also included in credit reports which can be purchased (e.g. by creditors or potential creditors) from Jordans Limited, a major UK business information provider. The credit scores range from 0 to 100 and are a measure of the likelihood that a company will become bankrupt in the next 12 months - with lower scores indicating higher failure risk. For company year ends commencing on or after 1 April 2014 (as per the company year ends in the current study), credit scores are allocated on the basis of a new[15] scoring model. The FAME online literature states that as well as financial data being used to determine credit scores, other factors taken into account include industry SIC data, director and shareholder information, county court

[13] FAME has a variable indicating whether a company has an audit. This variable was also checked with regard to small companies to ascertain if any had incorrectly filed unaudited small abbreviated accounts. None had done so.
[14] There was no obvious reason for this. It is possible that some of these companies had failed, but that this had not been recorded when the data was downloaded. It is also possible that the credit scorer had not yet allocated new credit scores.
[15] In the past, the database contained historical credit scores for prior accounting years. These have now been deleted from the FAME database. Similarly, for the new scoring model, historical credit scores are not available on the FAME database.

judgements and the timeliness with which a company files its accounts. *Inter alia*, the explanatory variables in the current study endeavour to capture all of these factors.

Table 5 about here

The experimental binary variables employed in the study are MICRO and REPACC, with the former coded 1 for micro companies filing abbreviated accounts and 0 for small companies filing abbreviated accounts. REPACC is coded as 1 if a company's annual accounts disclose they are prepared by an accountancy firm (as provided as a variable on FAME) and 0 otherwise. To check the accuracy of the FAME scanning process for this variable, and to ascertain the frequency with which an accountant's report is included in the annual accounts, the accounts filed at CH for random samples of 20 micro and 20 small companies (drawn from those reported in Table 6) where FAME indicated they had an accountant[16] were examined. In all cases, the name of the accountancy firm had been correctly scanned. The accounts of 11 companies (27.5%) contained an accountant's report, 6 of which were micro companies, with the remaining 5 being small ones. Typically, the accountant's name and address is included in the company information page under the heading 'Accountants', with the contents page indicating that the accounts contained an 'Accountant's Report'.

Following Dedman and Kausar (2012), the model includes control variables reflecting corporate size (which is expected to be positively associated with CREDSCR), gearing, liquidity, solvency and asset tangibility. More specifically, SIZE is the natural log of total assets, GEAR is the ratio of total liabilities to total assets, CACL is the ratio of current assets to current liabilities[17], NEGEQ (NEGWC) indicate that a company has negative equity (negative working capital) and FATA is the ratio of fixed to total assets. Theodossiou (1993) reports that the latter is negatively associated with corporate failure. As commented by Bessler, Drobetz and Kazemieh (2011, p. 24), 'a high ratio of fixed to total assets provides debtors with a high level of security since they can liquidate assets in case of bankruptcy'. For these reasons FATA is expected to be positively related to CREDSCR. Additional variables include whether a county court order for non-payment of debt has been issued against a company in the preceding 12 months (COURT); and whether FAME indicates that a

[16] The accounts of random samples of 12 micro and 12 small companies where no accounting firm name had been recorded on FAME were also checked. In all cases, no accountant's name appeared in the accounts.

[17] To mitigate the influence of outliers, values of GEAR and CACL are winsorised at a value of 3. Note that ratio values for FATA lie naturally in the range of zero to one.

company has defaulted (DEFLT) on its obligation to file its annual accounts/returns within prescribed time limits, thus incurring penalties (see e.g. Clatworthy and Peel 2016). In this context, Experian (2013) warns that late filing may lead to inferior credit ratings. Hence, both variables are predicted to be negatively related to CREDSCR, with COURT expected (intuitively) to have a particularly strong association.

A further variable (CHARGE) denotes whether a creditor has registered a charge against a company's assets. The presence of a registered charge has been found to be positively related to corporate failure (Wilson and Wright 2013). This may arise in cases of debt default, where secured creditors are more likely to instigate insolvency proceedings to recover the value of their collateralized loans. In this context, Wilson and Wright (2013, p. 956) note that a charge may be registered against high risk companies in order to mitigate default risk. In consequence, CHARGE and CREDSCR are expected to be negatively related. DIVERS is a binary variable denoting whether or not a company has more than one standard industrial classification code (i.e. operates in more than one industrial sector). Other things equal (and in line with portfolio theory), companies with diversified operations (revenue streams) may be perceived by the credit scorer to have a lower failure likelihood. If this is the case, a positive association between DIVERS and CREDSCR is anticipated.

As mentioned above, DUM5 represents a binary variable, where one (zero) denotes a company which had filed its fifth (second) set of annual accounts. If more mature companies are perceived to be associated with lower risk, then DUM5 and CREDSCR are expected to be positively related. As shown in Table 5, three variables focus on directors and shareholders[18]. Other things equal, companies with larger boards (LNDIR) have more human capital/resources to devote to managing their enterprises and in inconsequence may be less failure prone, thereby attracting higher credit scores. Similarly, *ceteris paribus*, companies with a larger number of shareholders (LNSHR) have a larger potential pool of equity finance to draw on and may thereby be less likely to fail. However, it is also possible that the credit scorer penalizes companies with a higher ratio of shareholders to directors (SHRDIR). This variable is a proxy for agency problems associated with the divorce between ownership and control may therefore be positively associated with corporate failure - and hence

[18] It is accepted that these are experimental variables and that ownership/governance variables may be more apposite for larger public/quoted companies with numerous/diverse shareholders (see e.g. Ashbaugh-Skaife *el al*. 2006).

negatively related to CREDSCR. Finally, as revealed in Table 5, with reference to their standard industrial classification (SIC) codes, nine industry dummy variables were computed.

As with the studies of Lennox and Pittman (2011) and Dedman and Kausar (2012), the hypotheses of this paper are evaluated with reference to empirical models estimated with FAME credit scores as the dependent variable. Note, however, that banks may utilise their own internal SME credit scoring systems (Resti 2016), though this does not preclude them from also referencing external credit scores such as those provided by FAME. Furthermore, a potential limitation of this study is that other UK company credit rating agencies (CreditSafe, Dun & Bradstreet, Equifax, Experian and Graydon UK) may formulate credit scores employing different criteria from FAME ones.

3.3 *Descriptive statistics*

Prior to focusing on the primary estimation samples, Table 6 presents descriptive statistics for the sample of all micro companies[19] (n=35,971) and the random sample of 40,000 small companies described previously. These descriptive statistics aim to provide a backdrop to the current study (as well as for potential future research) by reporting the stylized facts for the micro and small company sectors. For companies with total assets (TA) ≤ £316k, Panel A shows the mean values of CREDSCR, TA and REPACC for the micro and small subsamples, according to the number of annual accounts (YR) they had filed at CH since incorporation (ranging from 1 to ≥10). As reported, for all values of YR, the differences between the subsample means of the three variables are highly significant in all cases ($p \leq 0.001$), with micro companies being smaller, substantially less likely to have a reporting accountant and attracting lower credit scores than their small company counterparts. In general, the three variables increase with YR, though for both subsamples, this occurs only from Y6 for CREDSCR. More specifically, for micro (small) companies, mean values for CREDSCR, TA and REPACC rise from 22.15 (31.38), £20.34k (£32.11k) and 0.070 (0.358) for YR1 to 38.26 (51.48), £58.76k (£75.03k) and 0.153 (0.455) for YR10. As shown in the last column of Table 6, noteworthy is the lower credit scores systematically assigned to micro companies relative to small ones, with the difference in credit scores varying between -7.64 and -13.22.

Table 6 about here

[19] From the original sample of 35,983, 12 micro companies are omitted because they had voluntarily appointed auditors.

Panel B reports statistics for all companies with TA > £316k. Unsurprisingly, for both subsamples, it shows that the mean values of CREDSCR, TA and REPACC are substantially higher than those for companies with TA ≤ £316k. For the latter, Panel C presents results for a simple OLS regression model where CREDSCR is regressed on SIZE, REPACC, MICRO and nine binary YR variables (YR2 to YR10), with YR1 being the base (omitted) case[20]. As shown, the explanatory power of the model is reasonably high ($R^2 = 0.404$). Other than for REPACC, which exhibits a statistically insignificant (p=0.873) small negative coefficient which is close to zero (and thus not supporting *H2)*, the variable coefficients are highly significant ($p \leq 0.001$). After controlling for SIZE and YR, the coefficient for MICRO implies that, on average, the credit scores of micro companies are some 8.5 points lower than those of small companies. Hence, the OLS results in Table 6 are supportive of *H1*. For both subsamples, noteworthy is the pattern of the coefficients for the YR dummies, which suggest that credit scores increase from YR6 onwards[21]. Finally, Panel D shows that the market shares of the top five reporting accountants are relatively small. However, there is evidence of a higher degree of specialisation in the micro market, with the leading accountancy firms in the micro (small) company sectors being Carnegie Knox (SJD Accountancy) having market shares of 4.9% (1.9%).

Turning to the primary estimation samples, tables 5 and 7 provide summary statistics for the combined sample and the subsamples of micro and small companies respectively. As Table 5 shows, the mean total assets value (£42,877) of the sampled companies is comparatively small, as is the mean credit score (33.54), which varies from a minimum of 16 to a maximum of 69, with the median being 32. Consistent with the evidence presented in Table 1, the gearing (GEAR) sample mean of 0.966 is very high, though the median value is somewhat lower (0.858). In addition, a high proportion of companies exhibit negative equity (NEGEQ) and negative working capital (NEGWC), at 0.245 and 0.394 respectively.

Table 7 about here

As Table 5 reveals, 28.4% of companies disclosed that they had a reporting accountant, 1.4% had received a court order for non-payment of debt, 1.1% had defaulted with regard to filing their annual accounts

[20] Note that, given credit scores are not assigned to newly incorporated companies with negative equity, other things equal, YR1 mean credit scores would be expected to be even lower if the credit scorer had allocated credit scores to them.
[21] This would imply that the credit scorer penalises companies in the early part (to YR5) of their life cycle, when failure risk may be higher.

or returns on time and 3.6% had a charge registered against their assets. Of note is the large proportion of companies operating in the service sector (73.2%), with only 4.2% classified as being in the manufacturing sector. As anticipated, the mean ratio (0.984) of the number of directors to shareholders is approaching unity.

Using t-tests (chi-squared tests) for difference between variable means (proportions), Table 7 reveals that the small and micro subsamples differ significantly in a number of dimensions. Small companies are larger, are less likely to exhibit negative equity or to have received a court order for non-payment of debt. Micro companies exhibit higher liquidity (CACL), have higher asset tangibility (FATA) and are more likely to operate in more than one industrial sector (DIVERS). In addition, small companies have more shareholders and a higher ratio of shareholders to directors than micro ones. As also shown in Table 7, noteworthy, is that the proportion of small companies with reporting accountants (0.390) is substantially higher that for micro ones[22] (0.138). Given that micro companies opted to disclose less balance sheet information than their small company counterparts, this may result from them being less aware of (or less concerned with) the potential benefits[23] in terms of assurance/signalling. Furthermore, a significantly higher proportion of small companies (0.043) than micro ones (0.025) had a creditor's registered charge against their assets. It is likely that these charges contain restrictive covenants, one of which may be that a reporting accountant must be appointed. This would then contribute to the finding that small companies are more likely to have appointed a reporting accountant. Finally, the table reveals that the mean credit score of small companies (36.79) is 7.75 points higher (in percentage terms, 26.7% higher) than that of their micro counterparts (29.04).

Table 8 about here

Table 8 reports a Pearson's correlation matrix for the explanatory variables, together with CREDSCR. Most of the explanatory variable are significantly correlated with the latter and display their expected signs. On a univariate basis, MICRO and REPACC are negatively ($r = -0.340$) and positively ($r = 0.104$) associated with CREDSCR. GEAR and NEGEQ exhibit the highest degree of correlation with CREDSCR, with coefficients of

[22] The difference in proportions can be converted into an odds ratio by estimating the following simple logit model: MICRO = 0.022(Constant) - 1.384(REPACC). The odds ratio associated with REPACC is calculated as the exponential of the coefficient (-1.384) giving odds of 0.251:1.This implies that small companies are 3.98 times more likely (1/0.251) than micro ones to disclose they have a reporting accountant. This result holds after controlling for company size, as the following logit estimates reveal: MICRO =1.221(Constant) - 0.123(SIZE) - 1.349(REPACC). All model coefficients are significant at $p < 0.001$.

[23] Of course, more generally, as with voluntary audits, companies may choose not to hire a reporting accountant if the estimated cost is higher than the perceived benefits.

-0.460 and -0.412 respectively. As expected, the strongest correlations are between GEAR and NEGEQ (r = 0.774) and CACL and NEGWC (r = -0.732). However, as discussed below, there is no evidence that multicollinearity poses a problem in the regression models**.**

4. Empirical study

4.1 *Multivariate regression results*

Table 9 presents standard ordinary least squares (OLS) regression results with CREDSCR as the dependent variable. Model 1 reports the estimated parameters for the full model specification, with models 2 and 3 showing the stability of the parameters when insignificant variables are omitted. The reported variance inflation factors (VIFs) are a measure of the degree of correlation (collinearity) between each variable and the remaining variables. As shown, the VIFs are relatively low, with the highest being for GEAR (CACL) at 3.70 (3.03) respectively. In terms of collinearity, the statistical literature suggests VIFs exceeding 10 are unacceptable (Chatterjee and Price, 1991). Worthy of note is that Model 1 appears well determined, with an R^2 of 0.395, which is higher than the adjusted R^2 (0.286) reported by Dedman and Kausar (2012) for their cross-sectional credit score model. Consistent with *H1* and the univariate findings, the coefficient of MICRO is negative (-7.516) and highly significant (t= 47.64, p < 0.001).This implies that if micro companies had filed abbreviated accounts under the small company regime, on average, they would have benefitted from a 7.52 points rise (a 25.9% increase) in their credit scores.

Table 9 about here

However, unlike for audited accounts (Dedman and Kauser 2012), there is no evidence that the credit scorer rewards companies whose accounts bear the imprimatur of a reporting accountant. The coefficient of REPACC is negative[24] (-0.024) and indistinguishable from zero (t=0.13, p=0.898). Hence, *H2* is rejected. As described above, note that the simple regression model estimated in the extended samples (Panel C, Table 6) also supports this finding.

Model 1 shows that the shareholder/director variables and DIVERS are statistically insignificant, with DUM5 exhibiting a relatively small negative coefficient (-0.310), which is significant at the 10% level. The

[24] Though not investigated in the current study, it is highly unlikely that the credit scorer only awards a higher credit score to companies whose accounts contain an accountant’s report. If this was the case, REPACC would still be expected to attract a positive coefficient.

latter indicates that older companies that filed their fifth set of accounts have marginally lower credit scores than their younger counterparts who filed their second set of accounts[25]. LNSHR, LNDIR and SHRDIR are also statistically insignificant[26] when entered singularly or in pairs in Model 1. It is possible, however, that the credit scorer employs variables reflecting shareholder/director characteristics for larger (e.g. listed) companies where substantive agency/governance issues arise in consequence of the divorce between ownership and control (see Ashbaugh-Skaife, Collins and LaFond 2006).

The remaining control variables exhibit their expected signs and are statistically significant at the 1% level, other than for CHARGE which attains significance at the 5% level. In addition, on the basis of an F-test, the industry dummies are jointly significant ($p < 0.001$). As the table reveals, smaller companies with higher gearing, lower asset tangibility, lower liquidity, negative equity or negative working capital attract significantly lower credit scores. As anticipated, the coefficients of DEFLT, CHARGE and COURT are negative. Unsurprisingly, COURT has the largest association, with its coefficient implying that companies issued with a court order for non-payment of debt have a mean credit score some 11.74 points lower than those who had not received such a an order[27]. Models 2 and 3 show that the inferences for Model 1 are highly robust to the omission of the insignificant variables. Model 2 reveals that when LNSHR, LNDIR and SHRDIR are excluded, the remaining variable coefficients are similar in size and significance to their counterparts in Model 1. Similar findings obtain for Model 3, where all statistically insignificant variables are excluded. The latter parsimonious specification is therefore employed in the analysis reported in the following sections.

As mentioned previously, a number of companies which had not incurred current liabilities were excluded from the sample. As a robustness test, and following Black and Smith (2006), a dummy variable (NOCL) - coded 1 if a company has zero current liabilities (0, otherwise) - is included in the regression model. In addition, CACL is coded as zero for these missing observations. In the regression model, NOCL captures the mean difference in credit scores for companies not incurring current liabilities relative to those that did, whilst

[25] This result is consistent with the simple regression model reported in Table 6, which shows that credit scores increase monotonically with the filing of the sixth set of accounts onwards. This suggests a non-linear relationship between age and credit scores and therefore the DUM5 result is not necessarily inconsistent with the finding of Dedman and Kausar (2012) that company age is positively associated with credit scores.
[26] Similar results obtain when the number of directors and shareholders are employed in place of their logged values.
[27] Note, that the association between MICRO and CREDSCR is not insubstantial, the size of its coefficient amounting to 0.64 (7.52/11.74) of that for COURT.

facilitating the inclusion of all explanatory variables (including CACL) for the expanded sample. Appendix 1 to this paper reports regression results for the full specification. Though the coefficient for MICRO declines marginally to -7.30, Appendix 1 shows that the mean credit scores of companies without current liabilities (NOCL) is 1.78 points lower; and that the remaining variables exhibit similar signs and significance levels as their counterparts in Model 1. The OLS regression results are therefore robust to this specification change[28].

Finally, as discussed above, to examine the robustness of the regression results, Appendix 2 reports OLS models estimated separately for companies which had filed their second (Year 2) and fifth (Year 5) set of accounts. For both models, it shows that the control variables exhibit their expected signs and are statistically significant, other than for DEFLT and CHARGE which lose statistical significance in the Year 2 model. However, both are significant at the 10% level (p=0.08 and p=0.07 respectively) on the basis of a one-sided directional test. Importantly, the inferences for the experimental variables are stable across the year 2 and 5 models, with the coefficients for MICRO being -7.18 and -8.09 respectively; and with both being highly significant ($p < 0.001$). In contrast, the coefficients for REPACC are close to zero and statistically insignificant for both the Year 2 (t=0.15, p=0.883) and Year 5 (t=0.01, p=0.997) specifications. Hence these results strongly support those reported in Table 9. *Inter alia*, Section 4.5 discusses potential reasons for the statistical insignificance of REPACC; and hence the lack of empirical support for *H2*.

4.2 *Heckman selection models*

The Heckman treatment (endogenous selection) two-step model aims to control/test for unobserved selection bias (see e.g. Leuz and Verrecchia 2000, Tucker 2010, Bayar and Chemmanur 2012). In the current study, this would arise if an unobserved (hidden) variable is jointly and significantly correlated with CREDSCR and MICRO leading to biased estimates for MICRO. The rationale of the Heckman approach is that the errors (residuals) from a first-step probit selection model can be employed as a surrogate for potential hidden (omitted) variables. In the current study, a first-step probit selection model with MICRO as the dependent variable is used to compute generalised model residuals (Gourieroux *et al*. 1987), which are known as inverse Mills ratios (IMRs). The IMR for each company is then included in the second-step CREDSCR regression

[28] Similar results were found when this procedure was repeated for models 2 and 3 in Table 9, with the coefficients of MICRO being -7.298 and -7.292 respectively (both significant at $p < 0.001$).

specification (Model 3, Table 9) as a proxy for hidden variables. For credible implementation, an instrumental variable is required. Such a variable is a significant determinant of MICRO, but is not significantly correlated with CREDSCR, other than via its association with MICRO. In the current study, REPACC meets these empirical requirements. Table 10 reports Heckman two-step estimates employing the Stata *treatreg* command.

Table 10 about here

In consequence of the (unintended) sample distribution of DUM5 for small companies[29], three models are presented. As shown in Table 7, because the same number of small companies was randomly selected which had filed their second and fifth set of annual accounts, the proportion (0.5) filing their fifth set is overstated. Table 6 reveals that the actual proportion is around 0.34 (2,419/7,185). Table 10 therefore presents models including/excluding DUM5. In all cases, the IMR coefficients are statistically insignificant, suggesting that the standard regression results reported in Table 9 are preferred. For all probit models, the coefficients of REPACC are negative, stable and highly significant, with the reported Wald tests also confirming that REPACC is an effective instrumental variable[30].

As discussed above, the higher likelihood of small companies appointing a reporting accountant may result from these companies (or their accountants) being more aware of the associated potential benefits[31] (e.g. in providing a degree of assurance to banks and trade creditors). Importantly, the coefficient of the IMR (-0.299) in Model 1 is statistically insignificant (p=0.428), with the remaining variables exhibiting stable coefficients and significance levels when compared to the standard regression estimates in Table 9. Model 2 reports parameters where DUM5 is omitted from both the probit and OLS regression specifications. It shows that the estimated parameters[32] are similar to those in Model 1, with the coefficient of the IMR being identical to three decimal places - and exhibiting a similar level of insignificance (p=0.429). Finally, for completeness,

[29] Note this issue only affects the probit model and not the other regression models.
[30] Consistent with the univariate results, the other statistically significant probit model coefficients suggest that small companies are larger, are more highly geared, are less likely to exhibit negative working capital and are more likely to have a charge against their assets. Micro companies are associated with higher liquidity, higher asset tangibility and have a higher likelihood of displaying negative equity.
[31] The fact that micro companies chose not to file small company accounts may also indicate that they are less concerned about the potential benefits of having reporting accountant or of disclosing that fact. As highlighted in the Conclusion, further research is warranted into why companies appoint a reporting accountant.
[32] For direct comparison with the OLS results for Model 2, Model 3 in Table 9 was re-estimated with DUM5 omitted. The results are quantitatively similar to those for Model 3, with the coefficient for MICRO being -7.445 ($p < 0.001$).

Model 3 includes DUM5 in both the probit and OLS specifications. Its parameters are consistent with those reported for models 2 and 3. In summary, based on the Heckman estimates, there is no evidence of hidden selection (endogeneity) bias.

4.3 *Matching and regression adjustment*

Matching is an intuitive method which controls for potential observed bias associated with regression model estimates. More specifically, it does not rely on model functional form, nor does it require the linearity assumption, since estimates are confined to the common support; that is, where treated (in this study micro companies) and control subjects have similar characteristics[33]. Because it is usually impossible to match closely on more than one continuous variable (known as the curse of dimensionality), the method of propensity score matching (PSM) is widely employed in accounting studies (Tucker 2010). Rosenbaum and Rubin's (1983) seminal research demonstrates that matching on propensity scores (selection model probabilities) is equivalent to matching on the individual variables included in the selection model. Hence, PSM circumvents the curse of dimensionality. After PSM, the 'treatment effect' (in this study, MICRO) is estimated as a simple difference in the means of the outcome of interest in the matched samples (see e.g. Bayar and Chemmanur 2012).

As reported in Appendix 1, PSM is implemented with a probit selection model (with MICRO as the dependent variable), which contains the explanatory variables specified in Table 11. Using the Stata *psmatch* module, nearest neighbour (NN) matching without replacement is employed, where the predicted probability for each micro company is matched to the closest value of that predicted for a small company. To ensure close NN matching, a fine calliper of 0.01 is applied. This specifies the maximum difference in selection probabilities for micro and small companies which can be matched. As a robustness test, results are also reported where an even finer calliper (0.005) is applied.

Tables 11 and 12 about here

Table 11 reports covariate balance statistics for the NN matched micro and small companies for PSM with a 0.01 calliper (n= 8,710) and for the finer calliper of 0.005 (n=8,164). For both cases, it reveals that the

[33] Regression results may be biased if the linearity assumption does not hold outside the common support and/or if the model functional form is incorrect.

variable means are similar for the micro and small subsamples, with none of the differences approaching statistical significance at conventional levels. After matching, for the 0.01 (0.005) calliper samples, the mean credit scores for micro companies are 29.038 (29.067), compared to 37.015 (37.192) for small ones, with the mean differences of -7.977 (-8.125) being highly significant[34] (both at $p < 0.001$); and hence supporting *H1*.

As a robustness test, a typical approach in accounting research is to estimate regression models in the NN matched samples (e.g. Ittonen, Johnstone and Myllymäki 2015). Regression adjustment is applied for two reasons. Firstly, to account for any covariate imbalance after matching; and secondly, because estimates are doubly robust 'in the sense that if either the matching or the parametric model is correct, but not necessarily both, causal estimates will still be consistent' (Ho *et al*. 2007, p. 215). Using the same specification as Model 3 in Table 9 for the full sample, models 1 and 3 in Table 12 report standard regression results estimated in the NN matched samples. Both models exhibit the same patterns of coefficient signs and significance levels as their counterparts estimated in the full (unmatched) sample. In particular, the coefficients of MICRO are -7.868 (-7.999) for models 1(3), thus supporting *H1*.

Finally, the IMR for each matched company (estimated from Model 1 in Table 10 using the full sample[35]) is included as an additional variable in the NN matched regression specification. As with the full sample Heckman selection estimates, models 2 and 4 in Table 12 show that the IMR regression coefficients are statistically insignificant in the matched samples. In summary, results for the PSM and the adjusted regression models (with/without IMRs) support the full sample standard/Heckman regression findings. Furthermore, the estimates of the relationship between MICRO and CREDSCR reported in this section are similar to those of their full sample counterparts. In summary, there is no evidence of observed or unobserved bias.

4.4 *Further analysis: credit ratings*

As a further robustness test, this section extends the analysis to estimate models where the dependent variable is specified as companies' credit ratings. Based on credit scores, FAME assigns credit ratings on a five point ordered scale. Specifically, the ratings are defined in the FAME online literature as follows (with credit scores in parentheses): *Secure* (81 to 100): 'Companies in this sector tend to be large and successful public companies.

[34] The associated t-values are 36.54 (36.11).
[35] The Stata *treatreg* command enables IMRs to be saved as an additional variable in the dataset.

Failure is very unusual and normally occurs only as a result of exceptional changes within the company or its market'; *Stable* (61 to 80):'Here again, company failure is a rare occurrence and will only come about if there are major company or marketplace changes'; *Normal* (41 to 60): 'This sector contains many companies that do not fail, but some that do'; *Cautious* (21 to 40): 'Here, as the name suggests, there is a significant risk of company failure'; and *High Risk* (0 to 20): 'Companies in the high risk sector may have difficulties in continuing trading unless significant remedial action is undertaken, there is support from a parent company, or special circumstances apply'.

Using credit scores, companies were assigned into these categories on an ordered scale ranging from 1 = high risk to 4 = stable. Panel A in Table 13 shows the distribution of the credit rating for the full sample as well as for the micro and small subsamples. Unsurprisingly, no companies have scores in the secure rating category and only 17 are classified as being stable, 16 of which are small companies. As reported, the distributions of micro and small company credit ratings differ significantly, with a substantially larger proportion of small companies being in the lower risk categories.

Due to the difficulty in interpreting the effects of ordered probit model coefficients (Greene and Hensher 2009, p. 113), ordered logit models are often employed in accounting studies (e.g. Ashbaugh-Skaife *et al*. 2006, Altin, Kizildag and Ozdemir 2016). In particular, as shown below, the log odds coefficients of the ordinal logit model can be readily interpreted in terms of odds ratios (e.g. Yin and Zhang 2014). Panel B in Table 13 presents ordered logit models with identical (full and parsimonious) specifications to those which were used in the OLS credit score models reported in Table 9. Because of the small number of companies (and only one micro company) in the stable category, they are excluded from the analysis, so that the ordered dependent variable contains three rating categories[36]. As shown in Table 13, other than for DUM5 which is statistically insignificant, the full (Model 1) and parsimonious (Model 2) specifications exhibit the same coefficient signs and significance levels as their OLS counterparts; with the coefficient of REPACC in Model 1 again being close to zero (0.055) and statistically insignificant ($z=1.09$, $p= 0.277$). As models 3 and 4 reveal,

[36] Note, however, that similar results to those reported obtain when the models are estimated in the full sample (ordered ratings 1 to 4). For instance, for models 1(2), the coefficients of MICRO are -2.318 (-2.329), and are both highly significant at $p < 0.001$.

similar findings obtain when the estimates are confined to the two matched samples described above. Importantly, the coefficients of MICRO are stable and highly significant across all reported models.

Tables 13 and 14 about here

Taking the exponential of a logit coefficient gives its odds ratio. For the coefficient (-2.321) of MICRO in Model 1, the associated odds ratio is calculated as: exponential (-2.321) = 0.099:1. More specifically, after controlling for other factors, small companies are 10.1 times (1/0.099) more likely to be assigned a higher credit rating than their micro counterparts. This clearly demonstrates the negative influence of filing micro accounts on credit ratings, with the relationship being more pronounced than for the credit score models.

Controlling for potential unobserved selection bias with ordered outcome models is more complex than the Heckman approach. As explained by Miranda and Rabe-Hesketh (2006), though based on the same principles as the Heckman model (above), due to distributional assumptions, for consistent estimated parameters, it requires maximum likelihood simultaneous estimation of a probit selection model (Model 1, Table 10) and an ordered probit outcome model. In doing so, as with the Heckman approach, it accounts for correlated errors between the models. Using the Stata *ssm* command (Miranda and Rabe-Hesketh 2006), Table 14 presents endogenous ordered probit selection models, together with standard ordered probit model estimates for comparison. Model 1 shows that the standard ordered probit estimates are the same in terms of coefficient signs and statistical significance as the corresponding ordered logit ones. As explained by Greene and Hensher (2009, p. 114), in comparing the coefficients of ordered probit and ordered logit models, the relationship between the two is $\beta_{logit} \approx 1.81\beta_{probit}$. For the coefficient of MICRO in Model 1, the associated logit coefficient is: -1.196 * 1.81 = -2.165. This compares to the actual logit coefficient of -2.332 for the same specification (Model 2 in Table 13). Hence, there is a good degree of congruence between the models.

Model 2 reports the results for the endogenous ordered probit specification[37] It shows that the degree of correlation (rho) between the probit and ordered probit model errors (0.085) is statistically insignificant (p = 0.668).This result suggests that the standard ordered probit estimates for MICRO in Model 1 are apposite. For completeness, since DUM5 is statistically insignificant in all specifications, Model 3 omits this variable. As

[37] For brevity, the probit selection parameters are omitted. They are similar to those reported for Model 1 in Table 10.

shown, the estimates are similar to their Model 2 counterparts. Consistent with the Heckman model findings, the results presented in Table 14 indicate an absence of hidden selection bias. Finally, as per the OLS credit score models, Appendix 2 reports separate ordered logit specifications for companies which had filed their second (Year 2) and fifth (Year 5) set of accounts. The results are highly congruent with those reported above, with the coefficients of MICRO being highly significant and negative in both specifications - and being of a similar magnitude to those reported in Table 13 - and hence providing further empirical support for *H1*. Consistent with prior results relating to *H2*, the coefficients of REPACC are close to zero and statistically insignificant in the Year 2 (z=0.91, p=0.361) and Year 5 (z=0.68, p=0.496) models.

4.5 *Summary of results and study limitations*

In support of *H1*, this study finds systematic empirical evidence that companies filing micro accounts are associated with lower credit scores. In contrast, there is no empirical support for *H2*, in that REPACC is statistically insignificant in all the reported regression models, including the simple regression specification estimated in extended samples (Table 6). It is not unusual for archival accounting studies to report that empirical evidence does not support hypotheses/expected relationships (e.g. Liberty and Zimmerman 1986, DeFond, Raghunandan and Subramanyam 2002, Armstrong, Jagolinzer and Larcker 2010, Lawrence, Minutti-Meza and Zhang 2011, Minutti-Meza 2013). For instance, the influential study of Bowen, Burgstahler and Daley (1987) reports that, unlike for cash flows, there was no evidence to support the hypothesis that accruals have 'incremental information content relative to that contained in earnings' (p. 723). More recently, Vergauwe and Gaeremynck (2018) find that some conjectures relating to fair value disclosures and information asymmetry are not supported empirically. As with the aforementioned research, it is important that the veracity of empirical findings of the current research are examined across different samples[38]/jurisdictions and employing alternative methodologies (such as survey, interview and case study approaches).This is especially pertinent with regard to the current exploratory study, where (to the author's knowledge) the hypotheses have not been investigated in prior research.

[38] Using FAME credit scores, an example of this is the study of Dedman and Kausar (2012) which confirms the findings of Lennox and Pittman (2011), that voluntary audits are associated with superior credit scores. In addition, the method of meta-analysis is employed to evaluate empirical evidence from multiple studies with regard to outcomes/hypotheses (see Hay, Knechel and Wong 2006, for an accounting research example).

One potential explanation for the absence of empirical support for *H2* is that the credit scorer has not considered whether REPACC should influence credit scores. However, though this is a possible explanation (that the credit scorer has simply overlooked this variable), it is, perhaps, an unlikely one - given REPACC (whether a company has a reporting accountant) is readily available to the credit scorer as a variable on the FAME database. The fact that prior research (above) indicates that the FAME credit scorer gives cognisance to voluntary audits also makes this rationale less likely. A more plausible explanation is that the credit scorer has considered REPACC, but does not believe that the imprimatur of a reporting accountant carries sufficient weight (in terms of signalling/assurance) to warrant an upgrade in credit scores. This may occur if the credit scorer presumes that the statutory accounts of companies without reporting accountants have been prepared (at least largely) by accountants; and hence that the signalling/assurance value associated with REPACC is inconsequential. Specifically, in this case, though not knowing who prepared the accounts, it is conjectured that the credit scorer assumes that all (or for the most part) statutory annual accounts are prepared by accountants[39]. Note, however, that REPACC may provide some assurance for trade creditors, banks, tax authorities and other credit rating agencies.

Related to the above, in terms of sample design, this study focuses on young companies where information asymmetries are pervasive. In consequence (and as previously argued), any signalling/assurance value associated with the experimental variables is likely to be at its highest for companies in their start-up phase - and in consequence, empirically detectable. Despite this, it follows that a potential limitation of this study is that the empirical findings may not generalise to all small/micro companies. As already mentioned, further research is warranted to establish the validity of the empirical findings of this study; and especially with regard to reporting accountants. However, *a priori*, it seems unlikely that the credit scorer would fail to upgrade credit scores for companies with a reporting accountant in their start-up phase, when information asymmetries are at their most palpable, but (*ceteris paribus*) reward more mature companies with a reporting accountant when such asymmetries are less pronounced.

[39] Though not supported by the empirical results of this study, a counter argument is that if a credit scorer supposes that company accountants will only allow their name to appear on statutory annual accounts if they have prepared them, and/or consider they are accurate, then credit scores may be uplifted in line with the signalling/assurance tenets associated with REPACC.

A more general limitation of this study relates to causation. As with all studies which employ archival data, empirical inferences may not equate with causation. Strictly speaking, observational (non-experimental) studies cannot prove/establish causation, even when appropriate methods/models are used. Rather, the archival data used in the current study can be employed to establish whether hypotheses are supported in terms of the statistical association between variables.

5. Conclusion

Given it economic significance, the small business sector is one that continually exercises policy makers and attracts perennial government and statutory intervention. This is primarily aimed at encouraging entrepreneurship, new business formation and promoting and enhancing small firm growth. In the UK (and the EU) it also extends to 'lifting the burden' (costs) from small private companies of the requirements to file full annual accounts and to appoint an auditor. As described above, there is little evidence based policy regarding the deregulation of financial reporting requirements for small private companies (Singleton-Green, 2015). Though important, prior archival evidence concentrates on the influence of voluntary audits on credit scores and the cost and availability debt finance. In contrast, and given the dwindling market for voluntary corporate audits, this paper focuses on the vast majority of small UK companies which publish unaudited accounts, containing only an abbreviated balance sheet.

Consistent with signalling theory, this study finds that, relative to small companies filing abbreviated accounts, there is systematic evidence that the credit scorer penalizes companies which file micro-entity abbreviated accounts. This is consistent with the conjecture that the filing of micro accounts conveys a negative signal to the credit scorer that micro companies are of lower quality (higher risk). This finding is robust to statistical methods that accounts for both observed and unobserved (endogeneity) bias. Based on assurance and signalling tenets, the second conjecture examined in this paper is that companies which disclose their annual accounts are prepared by reporting accountant are expected to attract higher credit scores. However, contrary to extant research which reports that companies which opt for voluntary audits receive superior credit scores, there is no evidence that the credit scorer rewards companies whose accounts bear the imprimatur of a reporting accountant with better credit scores.

It is hoped the results of this exploratory study will stimulate further research in a wider context and across other jurisdictions. In particular, more qualitative and quantitative research is required into the motivation of small companies to file micro accounts and to appoint reporting accountants. In addition, research is required into whether small/micro companies which voluntarily publish fuller information in their annual accounts (including those that adopt higher financial reporting standards than those in FRS105 or Section 1A of FRS 102) benefit in terms of credit scores, debt finance and trade credit. In a similar vein, further archival and survey research is warranted into the potential benefits which may accrue to companies with reporting accountants. For instance, extant research reports that voluntary audits are associated with less costly debt finance (Kim *et al*. 2011), higher measures of financial reporting quality (Dedman and Kausar 2012) and fewer errors in statutory annual accounts (Clatworthy and Peel 2013). Such studies could be extended to examine whether these beneficial outcomes extend (though to an expected lower degree than obtaining to voluntary audits) to companies with a reporting accountant.

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Appendix 1: OLS and probit regression models

	OLS model	Probit model
MICRO	-7.299***	
REPACC	0.009	
SIZE	1.183***	-0.092***
GEAR	-1.968***	-0.025
CACL	1.980***	0.094***
NEGEQ	-3.179***	0.227***
NEGWC	-2.623***	-0.174***
FATA	4.923***	0.309***
COURT	-10.895***	0.141
DEFLT	-1.975***	-0.144
CHARGE	-1.012***	-0.113*
DIVERS	0.374	
DUM5	-0.287*	-0.486***
LNSHR	0.110	
LNDIR	-0.027	
SHRDIR	-0.105	
NOCL	-1.789***	
Constant	24.534***	0.434***
Industry dummies	✓	✓
R^2 or χ^2	0.411	758.34***
N=	14,483	13,102

Notes: Variables are defined in Table 5 in the paper. NOCL is a binary variable coded 1 if a company has zero current liabilities, 0 otherwise. As referred to in this paper, the dependent variable in the OLS model is CREDSCR and the model includes NOCL as an additional explanatory variable. As also referred to in the paper, the dependent variable for the probit model is MICRO. It is used to estimate the propensity scores (probabilities) for the matching analysis.
***,* Indicates coefficients are statistically significant at $p \leq 0.01$ and $p \leq 0.10$ (two-tailed tests).

Appendix 2: Regression models for companies filing their second and fifth set of accounts

	OLS credit score models[a]		Ordered logit credit rating models[a,b]	
	Year 2	Year 5	Year 2	Year 5
MICRO	-7.175**	-8.094**	-2.371**	-2.257**
REPACC	-0.036	0.001	0.064	0.049
SIZE	1.070**	1.322**	0.226**	0.275**
GEAR	-3.153**	-2.303**	-0.938**	-0.827**
CACL	1.916**	1.455**	0.204**	0.159**
NEGEQ	-3.099**	-2.692**	-0.715**	-0.411**
NEGWC	-2.051**	-3.359**	-0.794**	-0.990**
FATA	5.192**	5.945**	1.490**	1.472**
COURT	-10.665**	-13.682**	-9.264**	-7.332**
DEFLT	-1.204	-4.055**	-0.314	-1.451**
CHARGE	- 0.935	-1.111*	-0.419*	-0.134
Constant	26.201 **	24.258**		
Industry dummies	✓	✓	✓	✓
R^2 or χ^2	0.402	0.385	3,222.43**	2,271.12**
N=	7,607	5,495	7,607	5,478

Notes: All variables are defined in Table 5.
[a] Year 2 (Year 5) denote companies which had filed their second (fifth) set of accounts respectively.
[b] Credit ratings are 1 to 3 as per Table 13. Cut-off points (constants) are omitted.
**,* Indicate coefficients are statistically significant at $p \leq 0.01$ and $p \leq 0.05$ levels respectively; based on z-values for ordered logit models and t-values (robust standard errors) for OLS models (two-tailed tests).

Table 1. Summary gearing statistics for UK private independent companies for the corporate fiscal year to March 2017

Total assets (TA)	GEAR[a] Mean	WINGEAR[a,b] Mean	GEAR[a] Median	GEAR = 0[c] Mean	Negative equity[d] Mean
All companies (n=100,000)	1.384	0.839	0.768	0.022	0.185
TA $\leq$ £3.26m (n=98,331)	1.399	0.844	0.772	0.023	0.187
TA $\leq$ £316,000 (n=84,882)	1.527	0.885	0.808	0.025	0.203
TA > £3.26m (n=1,669)	0.551	0.550	0.562	0.007	0.063
TA > £316,000 & $\leq$ £3.26m (n=13,449)	0.586	0.581	0.571	0.004	0.089
TA > £100,000 & $\leq$ £316,000 (n=15,209)	0.642	0.627	0.590	0.006	0.117
TA $\leq$ £100,000 (n=69,673)	1.721	0.942	0.852	0.030	0.222

Notes: Data was downloaded in September 2017 from the FAME database. The sample of 100,000 companies was randomly selected from all (n=1,101,600) UK private independent (not held as a subsidiary) live companies (not failed/dormant) available on FAME.

[a] GEAR is defined as the ratio of total liabilities to total assets.

[b] WINGEAR denotes that GEAR values $\geq$ 3 are winsorised at a value of 3.

[c] The mean represents the proportion of companies that have zero values for total liabilities (GEAR = 0).

[d] The mean represents the proportion of companies that have negative equity (total liabilities > total assets).

Table 2. Micro and small company abbreviated balance sheets

Small company balance sheet†	Micro company balance sheet* (NR= not required)
Fixed assets	**Fixed assets**
Intangible assets	NR
Tangible assets	NR
Investments	NR
Current assets	**Current assets**
Stocks	NR
Debtors	NR
Investments	NR
Cash at bank and in hand	NR
Current liabilities (due within one year)	**Current liabilities** (due within one year)
Net current assets (liabilities)	Net current assets (liabilities)
Total assets less current liabilities	Total assets less current liabilities
Long-term liabilities (due after more than one year)	**Long-term liabilities** (due after more than one year)
Capital and reserves (Shareholders funds)	**Capital and reserves (Shareholders funds)**
Called up share capital	NR
Share premium account	NR
Revaluation reserve	NR
Other reserves	NR
Profit and loss account	NR

† Disclosure under The Small Companies and Groups (Accounts and Directors' Report) Regulations 2008.
* Disclosure under The Small Companies (Micro-Entities' Accounts) Regulations 2013.

Table 3. Reproduction of accountant's report

Note that the text in bold is as per the original report.

Chartered Certified Accountant's Report to the Directors on Unaudited Financial Statements of XX Limited

The following reproduces the text of the report prepared for the directors in respect of the company's annual unaudited financial statements, from which the unaudited abbreviated accounts have been prepared.

In order to assist you to fulfil your duties under the Companies Act 2006, we have prepared for your approval the financial statements of XX Limited for the year ended 31st October 2014 which comprise the Profit and Loss Account, the Balance Sheet, and the related notes from the company's accounting records and from information and explanations you have given us.

As a practising member firm of the Association of Chartered Certified Accountants, we are subject to its ethical and other professional requirements which are detailed at http://rulebook.accaglobal.com.

This report is made solely to the directors of XX Limited in accordance with our terms of engagement. Our work has been undertaken solely to prepare for your approval the financial statements of XX Limited and state those matters that we have agreed to state to the directors of XX Limited in this report in accordance with the requirements of the Association of Chartered Certified Accountants as detailed at http://www.accaglobal.com/factsheet163. To the fullest extent permitted by law, we do not accept or assume responsibility to anyone other than the company and its directors for our work or for this report.

It is your duty to ensure that XX Limited has kept adequate records and to prepare statutory financial statements that give a true and fair view of the assets, liabilities, financial position and profit of XX Limited. You consider that XX Limited is exempt from the statutory audit requirement for the year.

We have not been instructed to carry out an audit or a review of financial statements of XX Limited. For this reason, we have not verified the accuracy or completeness of the accounting records or information and explanations you have given to us and we do not, therefore, express any opinion on the statutory financial statements.

Accountancy firm name

Address

Date

Table 4. Sample construction

	Micro sample		Small sample		All companies	
	Lost	Remaining	Lost	Remaining	Lost	Remaining
Initial samples		6,996		8,000		14,996
Total assets > £316,000	(135)	6,861		8,000	(135)	14,861
Missing credit score	(59)	6,802	(76)	7,924	(135)	14,726
Has audited accounts	(3)	6,799		7,924	(3)	14,723
Disclosed profit and/or sales	(228)	6,571	(8)	7,916	(236)	14,487
Has negative gearing ratio	(4)	6,567		7,916	(4)	14,483
Current liabilities = zero	(1,069)	5,498	(312)	7,604	(1,381)	13,102

Table 5. Variable labels, definitions and means

Label	Definition	Mean (n=13,102)
CREDSCR	Credit score	33.535
MICRO	1= Filed micro abbreviated accounts, 0= filed small abbreviated accounts	0.420
REPACC†	1= Accounts disclose accountant's name (reporting accountant)	0.284
TA	Total assets (£)	42,877
SIZE	Natural log of TA	9.838
GEAR	Total liabilities to total assets	0.966
CACL	Current assets to current liabilities	1.374
NEGEQ†	1= Negative equity (total liabilities > total assets)	0.245
NEGWC†	1= Negative working capital (currents assets < current liabilities)	0.394
FATA	Fixed assets to total assets	0.199
COURT†	1= Court judgment for debt against company in past year	0.014
DEFLT†	1= Defaulted on filing annual accounts and/or annual returns on time	0.011
CHARGE†	1= Creditor has a registered charge against company assets	0.036
DIVERS†	1= Has additional standard industrial classification code	0.077
DUM5	1= Fifth set of accounts, 0= second set of accounts	0.419
LNSHR	Natural log of number of shareholders	0.149
LNDIR	Natural log of number of directors	0.246
SHRDIR	Number of shareholders to number of directors	0.984
AGRI†	1= Agricultural and fisheries industrial sector	0.004
MINING†	1= Mining industrial sector	0.002
MAN†	1= Manufacturing industrial sector	0.042
UTILI†	1= Utilities industrial sector	0.005
CONS†	1= Construction industrial sector	0.103
RET†	1= Retail/wholesale industrial sector	0.107
OTHSER†	1= Service industrial sector, other than financial services	0.712
FINSER†	1= Financial service industrial sector (base case)	0.020
NOIND†	1= If no standard industry code disclosed	0.007

Note:
† Indicates a binary variable where a company without the characteristic is coded as zero.

Table 6. Statistics for all micro companies and a random sample of 40,000 small companies

Panel A: Summary statistics

Years of Accounts (YR)	**MICRO:** means unbracketed, with number of companies bracketed			**SMALL**: means unbracketed, with number of companies bracketed			
	Total assets (TA) ≤ £316,000			Total assets (TA) ≤ £316,000			CREDSCR difference
	CREDSCR	TA £000	REPACC	CREDSCR	TA £000	REPACC	
YR1	22.15 (6,585)	20.34 (8,128)	0.070 (8,128)	31.38 (4,512)	32.11 (5,766)	0.358 (5,766)	-9.23
YR2	28.26 (4,846)	29.38 (4,895)	0.118 (4,895)	36.25 (4,766)	38.61 (4,804)	0.368 (4,804)	-7.99
YR3	27.90 (3,547)	35.44 (3,581)	0.134 (3,581)	36.76 (3,866)	44.62 (3,897)	0.389 (3,897)	-8.86
YR4	28.36 (2,588)	40.69 (2,618)	0.158 (2,618)	36.27 (3,023)	51.58 (3,049)	0.403 (3,049)	-7.91
YR5	28.12 (1,953)	42.74 (1,963)	0.144 (1,963)	36.31 (2,419)	52.25 (2,439)	0.382 (2,439)	-8.19
YR6	31.35 (1,663)	41.59 (1,685)	0.124 (1,685)	39.98 (1,843)	53.07 (1,864)	0.386 (1,864)	-8.63
YR7	34.91 (1,702)	45.52 (1,718)	0.137 (1,718)	44.69 (1,764)	57.29 (1,785)	0.406 (1,785)	-9.78
YR8	39.23 (1,929)	50.02 (1,946)	0.114 (1,946)	47.70 (1,819)	57.97 (1,831)	0.410 (1,831)	-8.47
YR9	39.97 (1,562)	52.02 (1,576)	0.108 (1,576)	47.61 (1,290)	64.32 (1,298)	0.423 (1,298)	-7.64
YR ≥10	38.26 (6,575)	58.76 (6,654)	0.153 (6,654)	51.48 (7,848)	75.03 (7,907)	0.445 (7,907)	-13.22
All years	30.69 (32,950)	38.69 (34,764)	0.120 (34,764)	40.99 (33,150)	52.35 (34,640)	0.398 (34,640)	-10.30
Panel B: TA > £316,000							
All years	40.63 (1,169)	775.39 (1,207)	0.253 (1,207)	56.90 (5,246)	1,251.55 (5,360)	0.471 (5,360)	-16.27

Panel C: Regression model (TA ≤ £316,000)

OLS (n=66,100): CREDSCR = 5.922(Constant) + 2.715SIZE - 0.018REPACC - 8.469MICRO + 4.631YR2 + 4.228YR3 + 3.740YR4 + 3.549YR5 + 6.969YR6 + 10.891YR7 + 14.295YR8 + 14.531YR9 + 15.383YR10   Model $R^2 = 0.404$

Panel D: Top 5 reporting accountants' market shares (TA ≤ £316,000)

MICRO (n=4,177)	**SMALL** (n=13,770)
Carnegie Knox: 4.93%	SJD Accountancy: 1.89%
Grant Harrod: 3.85%	Churchill Knight: 0.73%
Burrows Scarborough Silk: 3.14%	Paystream Accounting Services: 0.61%
Pipeline Accountants: 2.39%	Danbro Accounting: 0.54%
Limelight Accountancy: 2.38%	JSA Services: 0.47%

Notes: Variable definitions: SIZE = natural log of total assets (TA) and YR = number of annual accounts filed since incorporation. Panels A and B: mean values of CREDSCR, TA and REPACC differ significantly at $p < 0.001$ between the micro and small company samples on the basis of t-tests for CREDSCR and TA and χ^2 tests for REPACC (two-tailed tests) for individual years (YR) and for all years. Panel C: YR2 to YR10 are binary variables where unity corresponds to the number of annual accounts filed, with YR1 being the base case. On the basis of robust standard errors, all regression model coefficients are statistically significant at $p \leq 0.001$, other than that for REPACC which is statistically insignificant (p=0.873).

Table 7. Subsample variable means

	MICRO (n=5,498)	SMALL (n=7,604)
CREDSCR	29.038**	36.786**
REPACC	0.138**	0.390**
TA	36,702**	47,343**
SIZE	9.658**	9.969**
GEAR	0.976	0.958
CACL	1.405**	1.351**
NEGEQ	0.262**	0.233**
NEGWC	0.379**	0.405**
FATA	0.205**	0.195**
COURT	0.016*	0.012*
DEFLT	0.010	0.011
CHARGE	0.025**	0.043**
DIVERS	0.090**	0.070**
DUM5	0.305**	0.502**
LNSHR	0.132**	0.161**
LNDIR	0.243	0.248
SHRDIR	0.969**	0.995**
AGRI	0.004	0.003
MINING	0.001	0.002
MAN	0.045	0.040
UTILI	0.005	0.005
CONS	0.099	0.106
RET	0.103	0.109
OTHSER	0.722*	0.704*
FINSER	0.015**	0.023**
NOIND	0.007	0.007

Notes: All variables are defined in Table 5.
**,* Indicate means differ significantly between the MICRO and SMALL sub-samples at $p \leq 0.01$ and $p \leq 0.05$ on the basis of χ^2 tests for binary variables and t-tests for non-binary variables (two-tailed tests). No variables differed significantly at the 0.01 statistical level.

Table 8. Correlation matrix

	CREDSCR	MICRO	REPACC	SIZE	GEAR	CACL	NEGEQ	NEGWC	FATA	COURT	DEFLT	CHARGE	DIVERS	DUM5	LNSHR	LNDIR	SHRDIR
CREDSCR	1																
MICRO	-0.340*	1															
REPACC	0.104*	-0.276*	1														
SIZE	0.344*	-0.109*	0.111*	1													
GEAR	-0.460*	0.012*	-0.019*	0.378*	1												
CACL	0.367*	0.028*	-0.024*	0.272*	-0.650*	1											
NEGEQ	-0.412*	0.034*	-0.036*	-0.272*	0.774*	-0.472*	1										
NEGWC	-0.344*	-0.026*	0.008	-0.203*	0.576*	-0.732*	0.591*	1									
FATA	-0.057*	0.018*	-0.026*	-0.006	0.203*	-0.458*	0.208*	0.494*	1								
COURT	-0.149*	0.017*	-0.022*	-0.005	0.057*	-0.051*	0.055*	0.050*	0.062*	1							
DEFLT	-0.046*	-0.005	-0.005	-0.048*	0.042*	-0.040*	0.030*	0.015	0.016	0.025*	1						
CHARGE	0.016	-0.047*	0.037*	0.212*	0.028*	-0.062*	0.033*	0.057*	0.091*	0.033*	-0.012	1					
DIVERS	-0.015	0.045*	-0.039*	-0.047*	0.023*	0.009	0.031*	0.003	0.010	0.019*	-0.003	0.003	1				
DUM5	0.071*	0.197*	0.063*	0.135*	0.016	0.011	0.008	0.017*	0.003	-0.019*	-0.011	0.077*	0.018*	1			
LNSHR	0.054*	-0.043*	0.056*	0.172*	-0.017*	0.024*	-0.017	-0.015	0.018*	-0.029*	-0.021*	0.073*	0.013	0.062*	1		
LNDIR	0.026*	-0.006	0.003	0.106*	-0.001	0.012	0.002	-0.001	0.032*	-0.019*	-0.024*	0.069*	0.022*	0.133*	0.380*	1	
SHRDIR	0.018*	-0.025*	0.035*	0.066*	-0.001	0.003	-0.001	-0.003	-0.001	-0.005	-0.001	0.016	-0.010	-0.037*	0.588*	-0.369*	1

Notes: All variables are defined in Table 5 (n=13,102).
* Indicates correlation coefficient is significant at $p \leq 0.05$ (two-tailed tests).

Table 9. Credit score regression models

	VIF	Model 1	Model 2	Model 3
MICRO	1.137	-7.516	-7.514	-7.499
		(47.64)**	(47.59)**	(49.27)**
REPACC	1.102	-0.024	-0.025	
		(0.13)	(0.13)	
SIZE	1.366	1.170	1.170	1.164
		(18.23)**	(18.43)**	(18.43)**
GEAR	3.698	-2.766	-2.766	-2.766
		(17.95)**	(17.97)**	(17.97)**
CACL	3.028	1.724	1.724	1.731
		(11.64)**	(11.65)**	(11.71)**
NEGEQ	2.979	-2.967	-2.967	-2.959
		(11.93)**	(11.94)**	(11.92)**
NEGWC	2.869	-2.584	-2.583	-2.586
		(10.25)**	(10.25)**	(10.26)**
FATA	1.454	5.480	5.482	5.494
		(18.68)**	(18.69)**	(18.75)**
COURT	1.013	-11.740	-11.744	-11.727
		(21.07)**	(21.11)**	(21.11)**
DEFLT	1.006	-2.247	-2.250	-2.255
		(3.55)**	(3.56)**	(3.57)**
CHARGE	1.077	-0.995	-0.993	-0.985
		(2.48)*	(2.48)*	(2.46)*
DIVERS	1.015	0.426	0.427	
		(1.44)	(1.44)	
DUM5	1.081	-0.310	-0.304	-0.297
		(1.89)†	(1.87)†	(1.83)†
LNSHR	1.294	0.034		
		(0.64)		
LNDIR	1.613	0.091		
		(0.49)		
SHRDIR	1.378	-0.059		
		(0.48)		
Constant		25.611	25.555	25.617
		(26.33)**	(27.48)**	(27.57)**
Industry dummies		✓	✓	✓
R^2		0.395	0.395	0.395
N=		13,102	13,102	13,102

Notes: VIF = Variance inflation factor. All variables are defined in Table 5.
Coefficients are unbracketed, with t-values (based on robust standard errors) shown in parentheses.
**,* Indicate coefficients are statistically significant at $p \leq 0.01$ and $p \leq 0.05$ (two-tailed tests).
† Indicate coefficients are statistically significant at $p \leq 0.10$ (two-tailed tests).

Table 10. Heckman credit score selection models

	Model 1		Model 2		Model 3	
	OLS	Probit	OLS	Probit	OLS	Probit
SIZE	1.184	-0.085	1.170	-0.085	1.186	-0.063
	(17.59)***	(9.29)***	(17.49)***	(9.29)***	(18.10)***	(6.72)***
GEAR	-2.755	-0.059	-2.777	-0.059	-2.759	-0.020
	(13.67)***	(1.97)**	(13.80)***	(1.97)**	(13.71)***	(0.67)
CACL	1.718	0.045	1.706	0.045	1.708	0.064
	(12.15)***	(2.18)**	(12.08)***	(2.18)**	(12.03)***	(3.02)***
NEGEQ	-3.002	0.215	-2.992	0.215	-3.015	0.195
	(9.65)***	(4.71)***	(9.62)***	(4.71)***	(9.71)***	(4.22)***
NEGWC	-2.552	-0.183	-2.565	-0.183	-2.544	-0.160
	(9.52)***	(4.60)***	(9.57)***	(4.60)***	(9.51)***	(3.99)***
FATA	5.439	0.234	5.439	0.234	5.418	0.230
	(16.41)***	(4.87)***	(16.41)***	(4.87)***	(16.35)***	(4.72)***
COURT	-11.760	0.132	-11.735	0.132	-11.763	0.090
	(17.93)***	(1.35)	(17.90)***	(1.35)	(17.95)***	(0.91)
DEFLT	-2.233	-0.141	-2.224	-0.141	-2.220	-0.154
	(3.04)***	(1.28)	(3.02)***	(1.28)	(3.02)***	(1.38)
CHARGE	-0.958	-0.164	-0.991	-0.164	-0.961	-0.106
	(2.23)**	(2.47)**	(2.31)**	(2.47)**	(2.24)**	(1.58)
DUM5	-0.297				-0.177	-0.481
	(1.86)*				(0.92)	(20.23)***
MICRO	-7.044		-6.991		-6.845	
	(11.83)***		(11.76)***		(11.25)***	
Constant	25.292	0.519	25.334	0.519	25.182	0.409
	(25.49)***	(3.86)***	(25.53)***	(3.86)***	(25.57)***	(3.01)***
REPACC		-0.804		-0.804		-0.800
		(29.78)***		(29.78)***		(29.30)***
IMR	-0.299		-0.299		-0.427	
	(0.79)		(0.79)		(1.11)	
Industry dummies	✓	✓	✓	✓	✓	✓
R^2 or χ^2	0.395	1,252.03***	0.395	1,252.03***	0.395	1,666.13***
N=	13,102	13,102	13,102	13,102	13,102	13,102

Models 1 and 2: Wald test REPACC = 0; χ^2 = 887.01 ($p < 0.001$)
Model 3: Wald test REPACC = 0; χ^2 = 858.73 ($p < 0.001$)

Notes: All variables are defined in Table 5. IMR = the inverse Mills ratio. The dependent variables are CREDSCR and MICRO for the OLS and probit specifications respectively. Coefficients are unbracketed, with t-values (OLS) and z-values (probit) shown in parentheses. All models are estimated with the Stata *treatreg* command.
***,**,* Indicate coefficients are statistically significant at $p \leq 0.01$, $p \leq 0.05$ and $p \leq 0.10$ (two-tailed tests).

Table 11. Covariate balance (means)

	Matched propensity scores: calliper=0.01			Matched propensity scores: calliper=0.005		
	MICRO (n=4,355)	SMALL (n=4355)	Mean difference (p-value)†	MICRO (n=4,082)	SMALL (n=4,082)	Mean difference (p-value)†
SIZE	9.972	9.959	0.624	10.033	10.031	0.945
GEAR	0.955	0.934	0.161	0.951	0.931	0.192
CACL	1.344	1.357	0.517	1.340	1.350	0.586
NEGEQ	0.230	0.217	0.150	0.223	0.212	0.227
NEGWC	0.389	0.386	0.708	0.391	0.389	0.838
FATA	0.182	0.186	0.531	0.182	0.186	0.505
COURT	0.009	0.011	0.332	0.009	0.011	0.577
DEFLT	0.012	0.011	0.762	0.012	0.011	0.610
CHARGE	0.031	0.030	0.950	0.032	0.032	0.900
DUM5	0.385	0.385	0.982	0.410	0.410	1.000
AGRI	0.002	0.002	0.818	0.002	0.002	0.808
MINING	0.002	0.002	1.000	0.002	0.002	1.000
MAN	0.037	0.035	0.688	0.035	0.034	0.716
UTILI	0.005	0.006	0.554	0.005	0.006	0.545
CONS	0.104	0.103	0.916	0.104	0.104	0.942
RET	0.104	0.109	0.445	0.104	0.111	0.317
OTHSER	0.721	0.717	0.721	0.721	0.715	0.572
FINSER	0.019	0.018	0.937	0.020	0.019	0.936
NOIND	0.007	0.007	0.899	0.008	0.007	0.898

Notes: All variables are defined in Table 5.
† Difference between means probabilities (p-values) are based on χ^2 tests for binary variables and t-tests for non-binary variables (two-tailed tests). No means differ significantly at $p \leq 0.10$.

Table 12. Credit score regression models for propensity score matched samples

	Matched calliper p=0.01		Matched calliper p=0.005	
	Model 1	Model 2	Model 3	Model 4
MICRO	-7.868	-7.233	-7.999	-7.465
	(43.33)***	(10.66)***	(42.73)***	(10.75)***
SIZE	1.053	1.082	1.018	1.042
	(12.44)***	(12.06)***	(11.44)***	(11.11)***
GEAR	-2.582	-2.566	-2.554	-2.541
	(12.68)***	(12.56)***	(11.78)***	(11.68)***
CACL	1.931	1.915	2.050	2.036
	(10.25)***	(10.11)***	(10.40)***	(10.29)***
NEGEQ	-2.408	-2.468	-2.327	-2.378
	(7.86)***	(7.86)***	(7.24)***	(7.22)***
NEGWC	-2.977	-2.926	-3.071	-3.028
	(9.98)***	(9.68)***	(10.09)***	(9.83)***
FATA	6.285	6.206	6.651	6.586
	(15.85)***	(15.34)***	(15.92)***	(15.47)***
COURT	-13.453	-13.500	-13.506	-13.545
	(20.47)***	(20.52)***	(19.68)***	(19.72)***
DEFLT	-1.301	-1.272	-1.348	-1.324
	(1.79)*	(1.75)*	(1.84)*	(1.81)*
CHARGE	-1.067	-1.033	-1.049	-1.021
	(2.17)**	(2.09)**	(2.13)**	(2.06)**
DUM5	-0.641	-0.641	-0.774	-0.774
	(3.32)***	(3.32)***	(3.90)***	(3.90)***
IMR		-0.417		-0.351
		(0.98)		(0.80)
Constant	26.498	26.047	26.776	26.395
	(22.64)***	(20.72)***	(21.96)***	(20.25)***
Industry dummies	✓	✓	✓	✓
R^2	0.400	0.400	0.403	0.403
N=	8,710	8,710	8,164	8,164

Notes: All variables are defined in Table 5. IMR = inverse Mills ratio. Coefficients are unbracketed, with t-values (based on robust standard errors) shown in parentheses.
***,**,* Indicate coefficients are statistically significant at $p \leq 0.01$, $p \leq 0.05$ and $p \leq 0.10$ (two-tailed tests).

Table 13. Credit ratings and ordered logit models

Panel A: Distribution of credit ratings†				
	1: (High risk)	2: (Cautious)	3: (Normal)	4: (Stable)
MICRO	n=240 (4.37%)	n=4,968 (90.36%)	n=289 (5.26%)	n=1 (0.02%)
SMALL	n=192 (2.52%)	n=4,587 (60.23%)	n= 2,809 (36.94%)	n=16 (0.21%)
All	n=432 (3.30%)	n=9,555 (72.93%)	n=3,098 (23.65%)	n=17 (0.13%)
Panel B: Ordered logit models (credit ratings 1 to 3)				
	Model 1	Model 2	Model 3‡ PSM calliper=0.01	Model 4‡ PSM calliper=0.005
MICRO	-2.321***	-2.332***	-2.434***	-2.441***
REPACC	0.055			
SIZE	0.250***	0.249***	0.210***	0.209***
GEAR	-0.911***	-0.913***	-0.922***	-0.910***
CACL	0.172***	0.170***	0.158***	0.185***
NEGEQ	-0.550***	-0.550***	-0.543***	-0.514***
NEGWC	-0.887***	-0.886***	-0.932***	-0.926***
FATA	1.463***	1.457***	1.454***	1.492***
COURT	-8.311***	-8.306***	-9.037***	-8.936***
DEFLT	-0.714***	-0.712***	-0.393	-0.453
CHARGE	-0.214*	-0.214*	-0.302*	-0.311*
DIVERS	0.050			
DUM5	-0.027	-0.027	-0.076	-0.096
LNSHR	-0.035			
LNDIR	-0.002			
SHRDIR	-0.011			
Industry dummies	✓	✓	✓	✓
Model χ^2	5,557.66***	5,555.76***	3,483.99***	3,267.11***
N=	13,085	13,085	8,705	8,159

Notes: All variables are defined in Table 5. Coefficients are reported. Cut-off points (constants) are omitted.
† Distributions for MICRO and SMALL samples differ significantly: χ^2 =1,791.37 ($p < 0.001$).
‡ PSM = the propensity score matched samples employing callipers of p=0.01 and p=0.005 as reported in Table 12.
***,* Indicate coefficients are statistically significant at $p \leq 0.01$ and $p \leq 0.10$ levels respectively on the basis of z-values (two-tailed tests).

Table 14. Ordered probit and ordered probit endogenous selection models

	Credit ratings 1 to 3		
	1. Probit	2. Endogenous probit	3. Endogenous probit
MICRO	-1.196***	-1.323***	-1.321***
SIZE	0.134***	0.129***	0.128***
GEAR	-0.434***	-0.436***	-0.436***
CACL	0.132***	0.135***	0.135***
NEGEQ	-0.228***	-0.216***	-0.216***
NEGWC	-0.437***	-0.446***	-0.446***
FATA	0.755***	0.769***	0.769***
COURT	-4.100***	-4.083***	-4.083***
DEFLT	-0.403***	-0.408***	-0.408***
CHARGE	-0.122*	-0.130*	-0.131*
DUM5	-0.010	-0.009	
Industry dummies	✓	✓	✓
Model χ^2	5,280.77***		
N=	13,085	13,085	13,085
Rho†		0.085	0.085
Rho significance††		p=0.668	p=0.664

Notes: All variables are defined in Table 5. Coefficients are reported. Cut-off points (constants) are omitted. Using the Stata *ssm* module (Miranda and Rabe-Hesketh 2006), parameters for models 2 and 3 are obtained by jointly estimating, via maximum likelihood, the ordered probit models with a probit selection model (Model 1, Table 10).
† Rho is the estimated degree of correlation between the errors of the ordered probit model and the probit selection model.
†† Significance is with reference to a likelihood ratio test (Miranda and Rabe-Hesketh 2006).
***,* Indicate coefficients are statistically significant at $p \leq 0.01$ and $p \leq 0.10$ levels respectively, based on z-values (two-tailed tests).