A two-part fractional regression model for the capital structure decisions of micro, small, medium and large firms.

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Resumo/Abstract:

A key theme in corporate finance has been the study of the main factors that affect the financing decisions of firms. In this paper we examine the following two hypotheses which traditional theories of capital structure are relatively silent about: (i) the determinants of capital structure are different for micro, small, medium and large firms; and (ii) the factors that determine whether or not a firm issues debt are different from those that determine how much debt it issues. Using a binary choice model to explain the probability of a firm raising debt and a fractional regression model to explain the amount issued, we find strong support for both hypotheses. Nevertheless, the pecking-order theory seems to be suitable to describe the capital structure choices made by all size-based groups of firms.

Palavras-chave/Keyword: Corporate finance, capital structure, leverage, micro firms, SMEs, fractional data, two-part model.

Classificação JEL/JEL Classification: C51, G32
1 Introduction

Ever since Modigliani and Miller’s (1958) pioneering contribution to the capital structure literature, a key theme in corporate finance has been to identify the main factors that affect the financing decisions of firms. For many years, most theoretical and empirical research on capital structure has focussed on large, listed firms. However, it is widely recognized today by scholars and policymakers that small and medium enterprises (SMEs) play a key role in economic and social development throughout the world. In Europe, the increasing attention dedicated to their role in the economy is clearly illustrated by the European Charter for Small Enterprises approved by the European Union leaders in 2000, where it is recognized that ‘small enterprises must be considered as a main driver for innovation, employment as well as social and local integration’. In the European Union, in 2003, SMEs represented 99.8% of all enterprises and contributed about 69.7% of employment and 57.3% of turnover (European Commission 2003).

Thus, in recent years there has been a substantial increment in the number of empirical studies on SMEs’ debt policy decisions; see inter alia Cassar and Holmes (2003), Michaelas, Chittenden and Poutziouris (1999), Sogorb-Mira (2005) and Watson and Wilson (2002). Similarly to these authors, our main aim in this paper is to investigate whether and to what extent the existing capital structure theories provide also a satisfactory account of the capital structure choice of SMEs. However, besides being the first major investigation of the main determinants of capital structure in Portugal, our approach differs from theirs in two main aspects.

First, the data set that we use in this study comprises (using the new definitions recently adopted by the European Commission) large, medium, small and micro firms, which allows us to make an integrated study and comparison of the main determinants of the capital structure of each one of those four size-based groups. In contrast, most previous studies on SMEs: (i) do not distinguish between micro, small and medium firms, treating all SMEs as a unique, uniform group and, thus, ignoring that different factors might affect their capital structure choices in fundamentally different ways; (ii) use arbitrary definitions of SMEs; and (iii) use data sets covering only SMEs, which implies that all comparisons made in those papers with large enterprises (LEs) capital structure decisions are based on results for LEs described in other studies, which were obtained using other data sources and, sometimes, other econometric methodologies and frequently are relative to other countries and time

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1The European Charter for Small Enterprises is available online at http://europa.eu.int/comm/enterprise/enterprise_policy/charter/docs/charter_en.pdf.
spans. Moreover, note that the micro firm group per se clearly deserves a special attention. Indeed, according to European Commission (2003), within the group of European SMEs, the vast majority (92.5%) are micro enterprises, which contribute to 56.5% of the employment generated by SMEs. Similar patterns may be found around the world. However, to the best of our knowledge, there are no studies on the capital structure of micro firms.3

The second major difference between our paper and other empirical analysis of SMEs’ financing decisions concerns the econometric methodology employed, which is another important contribution of this paper. In particular, we show that the standard practice of using linear regression models to examine how a given set of potential explanatory variables influence some leverage (debt to capital assets) ratio is simply not appropriate. Indeed, since, by definition, a leverage ratio is observed only on the closed interval [0,1] and many firms have null leverage ratios, the effect of any explanatory variable on leverage ratios cannot be constant throughout its entire range.4 This is a critical issue since misspecification of the functional form of a regression model leads to results that are of little use. Nevertheless, this question has been completely neglected in the capital structure empirical literature hitherto; see, for example, Frank and Goyal (2006), which discuss several econometric issues that may affect the regression analysis of leverage ratios (e.g. missing data, surviving bias, outliers) but ignore that the bounded nature of leverage ratios conditions crucially the range of approaches that can be adopted for modelling them.

Given that linear models are unsuitable for explaining leverage ratios, the empirical analysis undertaken in the paper is based on the (nonlinear) fractional regression model developed by Papke and Wooldridge (1996) for continuously measured proportions with a finite number of boundary observations (i.e. 0s and 1s). As this model takes explicitly into account the restrictions on the values of leverage ratios,

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2This last criticism does not apply to some recent empirical studies which, although not focussing on SMEs, started to include robustness tests on firm size, reestimating their main models for size-based sub-samples; see inter alia Frank and Goyal (2005) and Flannery and Rangan (2006). However, the other two remarks still apply to these studies and, in addition, they consider only listed firms which, clearly, do not represent the majority of SMEs at all. Indeed, even the smallest of traded firms is large relative to most of the firms in the economy.

3Somewhat related papers to the study of the capital structure of micro firms are those examining the financing decisions of family business owners (e.g. Romano, Tanewski and Smyrnios 2000) since many micro firms are indeed family businesses. However, many family businesses cannot be classified as micro enterprises.

4Actually, there are two exceptions to this case: (i) some firms may have negative book values of equity, implying leverage ratios higher than 1; however, such firms are typically excluded from empirical studies on capital structures; and (ii) a small number of earlier applications focussed on debt to equity ratios, which are not bounded from above; however, using linear regression models to explain such ratios is still not appropriate since the (high) number of firms with null leverage ratios remains the same.
it could be directly applied to our data. However, based on a preliminary analysis of our data, we decided to develop and apply a two-part fractional regression model that treats separately the decision of issuing debt or not and, conditional on this decision, the decision on the quantity of debt to issue. Indeed, when we first examined the data, we found a very interesting fact: while the proportion of firms that do not use debt financing is higher for micro firms, conditional on having debt this is also the group of firms that present the largest average leverage ratio. Moreover, in both cases small firms are ranked in second place, medium firms in third and large firms in fourth. As, clearly, this suggests that the factors that determine whether or not a firm uses debt at all are different from the factors that determine how much debt are used by firms that do use debt, it seemed more realistic to allow the explanatory variables to influence in independent ways each decision. Therefore, in our empirical analysis the first decision is modelled as a binary choice model and the second as a fractional regression model that explains the amount of debt issued conditional upon the decision to issue debt.

The remainder of this paper is organized as follows. In section 2 we briefly review some capital structure theories and the main empirical hypotheses that are implied by those theories about a firm’s capital structure choice. Section 3 describes the data set used in our study and formulates the two main hypotheses that are examined in this paper. Section 4 explains the econometric methodology applied to the data. Section 5 presents the empirical results. Finally, section 6 summarizes and concludes the paper.

2 Standard determinants of capital structure

2.1 Alternative theories

Three of the most popular explanations of capital structure are the trade-off, the agency costs, and the pecking-order theories. Below we give a brief overview of each one of these theories; for more details see the recent surveys by Frank and Goyal (2006) and Prasade, Green and Murinde (2005).

The trade-off theory (TOT) claims the existence of an optimal capital structure that firms have to reach in order to maximize their value. The focus of this theory is on the benefits and costs of debt. The former include essentially the tax deductibility of interest paid (Modigliani and Miller 1958), while the latter are originated by an excessive amount of debt and the consequent potential bankruptcy costs (Kraus and Litzenberger 1973). Thus, firms set a target level for their debt-equity ratio that balances the tax advantages of additional debt against the costs of possible financial
distress and bankruptcy.

The agency costs theory (ACT), initiated by Jensen and Meckling (1976), states that the optimal capital structure of each firm depends on the value of debt that mitigates the conflicts between stockholders and managers, on the one hand, and stockholders and bondholders, on the other hand. According to this theory, the stockholder-manager agency costs of free cash-flow push firms towards more debt in order to reduce the ‘free’ cash at managers’ disposal (Jensen 1986), while the stockholder-bondholder agency costs of underinvestment and asset substitution push firms towards less leverage since large debt levels may be an incentive for rejecting value-increasing projects (Myers 1977) and pursuing risky projects (Jensen and Meckling 1976).\(^5\)

The pecking-order theory (POT), which was originally developed by Myers (1984) and Myers and Majluf (1984), on the other hand, argues that firms do not possess an optimal capital structure although the financing decisions of their managers are not irrelevant for their value. Indeed, due to information asymmetries between firms’ managers and potential outside financiers, which limit access to outside finance, firms tend to adopt a perfect hierarchical order of financing: first, they use internal funds (retained earnings); in case external financing is needed, they issue low-risk debt; only as a last resort, when the firm exhausts its ability to issue safe debt, are new shares issued. In the absence of investment opportunities, firms retain earnings and build up financial slack to avoid having to raise external finance in the future. Hence, the firm leverage at each moment merely reflects its external financing requirements without a tendency to revert to any particular capital structure.

### 2.2 General empirical hypotheses

The three capital structure theories just described allow the identification of various factors as determinants of a firm’s capital structure choice. Based on them, we next formulate a number of hypotheses for firms’ financing decisions which are standard in the financial literature. In each case, we indicate briefly which and why a particular theory claims such behaviour, and provide some references where more detailed argumentation can be found.

1. **Non-debt tax shields are negatively related to debt.** Tax deduction for depreciation and investment tax credits act as substitutes for the tax benefits of debt,

\(^5\)Note that some authors consider the ACT as a part of the TOT since it focusses also on the benefits and costs of debt. However, in contrast to tax-based and bankruptcy theories, which are inter-dependent, the ACT originates a complete theory of capital structure, so we opted for considering it separately.
which implies that a firm with a large non-debt tax shield is likely to be less leveraged (TOT - DeAngelo and Masulis 1980).

2. **Collateral is positively related to debt.** Firms with a greater percentage of their total assets composed of tangible assets have a higher capacity for raising debt since, in case of liquidation, these assets keep their value (TOT - Myers 1977). In firms with large tangible assets and poor cash-flows, stockholders may be better off by liquidating current operations; as managers may always want to continue the firm’s current operations, debt can be considered a mechanism to increase default probability and give debt-holders the option to force liquidation (ACT - Harris and Raviv 1990). Due to asymmetric information, it is easier for the lender to establish the value of tangible assets, so firms with larger proportion of tangible assets have better access to the debt market (POT).

3. **Size is positively related to debt.** Larger firms tend to be more diversified, so their probability of bankruptcy is relatively smaller; moreover, large firms are more likely to have a credit rating and, thus, access to non-bank debt financing (TOT - Warner 1977). As informational asymmetries are less severe for larger firms, they find it easier to raise debt (POT - Myers, 1984).

4. **Profitability is:**
   
   (a) **positively related to debt.** The higher the profitability of the firm, the higher the tax advantages of using debt and the less the probability of failing its interest payments (TOT) and the higher the free cash flows of the firm and the agency costs of equity, so a higher level of debt should be used to discipline the behaviour of management (ACT - Jensen and Meckling 1976).
   
   (b) **negatively related to debt.** The more profitable the firm, the greater the availability of internal capital, the less the need for external funds (POT - Myers 1984).

5. **Expected growth is:**
   
   (a) **negatively related to debt.** As financial distress is more costly for firms with large expected growth prospects, firms may be reluctant to take on large amounts of debt in order to not increase their bankruptcy probability (TOT - Myers 1984). Firms with more investment opportunities have
less need for the disciplining effect of debt payments to control free cash flows (ACT - Jensen 1986).

(b) **positively related to debt.** Firms with more investment opportunities borrow more since their probability of outrunning internally generated funds is larger (POT - Shyam-Sunder and Myers 1999).

6. **Age is:**

(a) **positively related to debt.** The longer the firm’s history of repaying its debt, the lower will be its borrowing cost since lenders believe firms will not engage in asset substitution projects (ACT - Diamond 1989).

(b) **negatively related to debt.** Older firms tend to accumulate retained earnings and, thus, require less external finance (POT - Petersen and Rajan 1994).

7. **Liquidity is negatively related to debt.** If firms prefer internal sources of finance, they tend to create liquid reserves from retained earnings in order to finance future investments, which reduces their need for external funds (POT - Myers and Majluf 1984).

Clearly, TOT, ACT, and POT are not mutually exclusive since some of the hypotheses stated can be easily accommodated in two or even the three theories. Therefore, empirically, distinguishing among these theories has proven very difficult. Indeed, as Shyam-Sunder and Myers (1999) show, many of the current empirical tests lack sufficient statistical power to distinguish between the theories. Moreover, Strebulaev (2006) has recently shown that because firms refinance infrequently and are not always at a refinancing point, reduced-form empirical evidence usually interpreted as refuting the trade-off theory may be actually consistent with a dynamic version of this theory. Thus, although the evidence found later in section 5 seems to be clearly in favour of one of the theories discussed above, the reduced-form capital structure study undertaken in this paper does not allow us to be entirely sure about which theory, if any, best describes the financing behaviour of Portuguese firms. However, that is not the aim of this paper, as discussed next.

### 3 Data and main hypotheses of the paper

A preliminary analysis of our data leads us to formulate two further hypotheses which the three theories of capital structure considered above are relatively silent
about. In this section we first describe the data set used in our study and then we discuss the additional hypotheses that will be investigated.

3.1 Sample and variables

The data used in this study were provided by the Banco de Portugal Central Balance Sheet Data Office (CBSDO). From the CBSDO database we drew some information about balance sheets, income statements and other characteristics of many non-financial Portuguese firms for the year 1999.\(^6\) In order to eliminate firms which were temporarily unoperational, or in the very early or very late stages of business operations, we discarded all firms with zero sales or negative earnings before interest, taxes and depreciation. Firms with negative equity and 4 huge outliers were also excluded. This selection criteria produced a final sample of 4692 firms.

Unlike most of the previous studies (the only exception seems to be Sogorb-Mira 2005), in this paper we use objective definitions of micro, small and medium firms, namely the new definitions adopted by the European Commission (recommendation 2003/361/EC). Thus, the category of SMEs consists of enterprises which employ fewer than 250 persons and have either an annual turnover not exceeding 50 million euros, or an annual balance sheet total not exceeding 43 million euros. Within this group, small enterprises are defined as firms which employ fewer than 50 persons and whose annual turnover or annual balance sheet total does not exceed 10 million euros. Finally, micro enterprises are defined as firms which employ fewer than 10 persons and whose annual turnover or annual balance sheet total does not exceed 2 million euros. Panel A of Table 1 contains the breakdown of our sample by firm size.

### Table 1 about here

In this paper we use as measure of financial leverage the ratio of long-term debt (LTD) to long-term capital assets (defined as the sum of LTD and equity); see Rajan and Zingales (1995) for an extensive discussion on these and other alternative measures of leverage. LTD is defined as the total company’s debt due for repayment beyond one year. We use book values of both LTD and equity since our sample comprises mostly unlisted firms. We consider only LTD because the focus of all capital structure theories is the option that firms make between LTD and equity to finance their businesses. As our aim in this paper is to investigate whether those

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\(^6\)Most authors argue that the capital structure of financial corporations must be analyzed separately because their financial responsibilities are not strictly comparable with those of other firms; see for example Rajan and Zingales (1995, p. 1424).
theories apply to all size-based groups of firms, we do not consider all the other possible financing alternatives of firms such as short-term debt and trade credit, which tend to be important particularly for smaller firms.

As most of the factors that appear in the seven hypotheses formulated in section 2.2 correspond to unobservable theoretical attributes, in the econometric analysis undertaken later in the paper we use some explanatory variables that work as proxies for those attributes. The ones that we chose, which have been widely used in the empirical literature, are described in Table 2. We also made some experiments with other proxies but the results obtained will not be reported since they were very similar. Some descriptive statistics for the explanatory variables are reported in Table 3.

Table 2 about here
Table 3 about here

3.2 Firm size and debt financing

Originally, the three theories of capital structure reviewed in section 2.1 were formulated to explain the observed practices of large, publicly traded corporations. One of the main aims of this paper is to investigate whether they are also appropriate to identify the main factors that affect the financing decisions of micro, small and medium firms, namely their option between LTD and equity.\(^7\) In fact, there has been an increasing recognition that SMEs are not just ‘scaled down’ versions of large firms: they differ in basic aspects (e.g. taxability, ownership, flexibility, industry, economies of scale, financial market access, level of information asymmetry, etc.; see Scherr and Hulbert 2001) that influence numerous aspects of their performance, including possibly their choice between LTD and equity financing. Similarly, in this paper we conjecture that the SME group is not homogeneous at all and that the smallest size-based groups are not just scaled down versions of the others.

There seem to be various reasons why traditional capital structure theories may not apply directly to (at least the smallest size-based sub-groups of) SMEs. One of those reasons is the informational opacity of most SMEs (see inter alia Berger and Udell 1998). For example, in general, SMEs do not enter into contracts that are publicly visible or widely reported in the press and do not issue traded securities that are continuously priced in public markets and therefore have no objective

\(^7\) Actually, in the case of smaller firms the option is basically between long-term bank or private debt and internal equity since typically small businesses do not get financing from stock and bond issues.
basis for valuation. Moreover, many of the smallest firms do not have audited financial statements that can be shared with any provider of outside finance. As a consequence, SMEs may have difficulty building reputations to overcome their informational opacity and, hence, their access to external funding tends to be limited. Indeed, in general, SMEs are not able to obtain credit in public debt markets and have to depend on financial intermediaries, particularly commercial banks, which may not be willing to provide them all the funding they need. Actually, the smaller the firm, the larger tends to be its difficulty in raising debt.

On the other hand, even in the absence of debt supply constraints, smaller firms are less prone to use debt financing and more likely to use ‘internal’ equity. Indeed, many small firms are family businesses that do not pursue any high growth strategy and arguments like "being one’s own boss" may be prominent in the entrepreneur’s objective function, which implies that such firms may not need or wish to use debt financing. Moreover, due to poor management skills, owners of small firms may be unable to understand the benefits of debt and the appropriate form of capital, revealing a strong preference for those financing options that minimize intrusion in their businesses, i.e. their ‘own’ money (retained earnings and personal savings). Thus, the smaller the firm, the larger seems to be their probability of not using debt by choice.

Therefore, it appears that both supply- and demand-side effects lead smaller firms to use less proportion of debt in the financing of their activity than predicted by traditional capital structure theories for large firms. Instead, they have to and choose to use more (internal) equity. The analysis of Panel B of Table 1 seems to confirm our conjecture. Indeed, as implied by the discussion above, there is a clear size effect on the probability of a firm using LTD, with larger firms resorting to LTD more often than smaller firms: the percentage of firms that do not have LTD is 88.7%, 76.8%, 51.2% and 40.6% for the groups of micro, small, medium and large firms, respectively. Although we are not aware of comparative figures for other countries (most empirical studies do not report the proportion of firms that do not use LTD, both in global terms and by size category), the few statistics reported in other papers lead us to believe that this size effect is not exclusive of Portugal and, actually, is valid for most countries. For example, in Petersen and Rajan (1994), based on U.S.A. data, and Brounen, Jong and Koedik (2005), which uses data from U.K., France, Germany and Netherlands, it is also evident that larger firms tend to use LTD more frequently.

Therefore, given that smaller firms are clearly less prone to use LTD, in this paper we formulate and test the following hypothesis:
8. *Determinants of debt are different for micro, small, medium and large firms.*

In particular, we test whether the seven factors listed in the previous section are important for the capital structure decisions of the four size-based group of firms considered in this paper and whether their influence is similar in all cases.\(^8\) To the best of our knowledge, no empirical study has been dedicated to the investigation of this hypothesis so far.

### 3.3 To issue or not to issue debt versus how much debt to issue

Given the clear differences in the proportion of firms that use LTD in each category, it is not surprising that the same size effect is apparent when we compare mean and median leverage ratios by category (panel C): typically, larger firms have larger leverage ratios. However, when we limit our comparison to firms that have LTD (panel D), we find contradictory results: once they decide to use LTD, smaller firms seem to use it in larger amounts than larger firms. For each one of the six possible pairs of size-based groups of firms, we tested the statistical significance of the differences between: (i) the proportion of firms that use LTD in each category; and (ii) the mean leverage ratios of each category considering only firms that use LTD. In both cases, the tests revealed significant differences at a 1% level for all the six pairs of groups of firms. Thus, firm size seems to affect in an inverse way the decisions on: (i) to issue or not to issue debt; and (ii) (for those firms that do decide to use debt) on how much debt to issue. Based on this finding, we conjecture that those decisions are taken independently from one another and, hence, some factors may affect in different forms (at least in magnitude) each decision. Therefore, in this paper we examine also the following hypothesis:

9. *The mechanisms that determine whether or not a firm uses debt at all are different from the mechanisms that determine how much debt is used by firms that do use debt.*

To test this hypothesis we develop in section 4.3 an econometric model that recognizes the possibility that the mechanisms for each decision are different. Basically, we model separately the probability of a firm using debt and the expected

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\(^8\)Note that size is included in two different ways in our analysis, both as a quantitative variable (sales) and as a nominal variable (size-based group of firms). Indeed, the effects of size, as measured by sales, on the capital structure of firms may vary depending on whether the firm is in fact micro, small, medium or large-sized.
value of the amount of debt used by a firm when it does use debt. Apart from Cook, Kieschinick and McCullough (2004), all previous empirical studies on capital structure have imposed the restriction that the factors that influence whether or not a firm uses debt have exactly the same influence on how much debt the firm uses.

4 Econometric methodology

In this section we first discuss why standard regression models are not suitable for modelling leverage ratios, then we briefly review Papke and Wooldridge’s (1996) regression model for fractional data, and finally we present the two-part fractional regression model developed in this paper.

4.1 Why standard regression models are not appropriate for modelling leverage ratios

Typically, empirical studies of capital structure use linear regression models to explain observed leverage ratios, which are then estimated by least squares-based (LS) methods using cross sectional or panel company data; see for example the recent surveys by Frank and Goyal (2006) and Prasade, Green and Murinde (2005), which summarize the main methodologies used in capital structure empirical research. However, leverage ratios have two fundamental statistical properties that cannot be ignored econometrically: (i) by definition, they are bounded between 0 and 1; and (ii) many firms do not use debt in their financing. Therefore, since the effect of any explanatory variable cannot be constant throughout its entire range, the linearity assumption

\[ E(Y|X) = X\beta, \]

where \( Y \) is the dependent variable (a leverage ratio), \( X \) denotes a matrix containing all explanatory variables and \( \beta \) is the vector of variable coefficients that we aim to estimate, is unlikely to hold. Moreover, specification (1) cannot guarantee that the predicted values of \( Y \) lie between 0 and 1 without severe constraints on the range of \( X \) or ad hoc adjustments to fitted values outside the unit interval.

\[ \text{For example, 72.8\% of the firms in our sample have null leverage ratios. Petersen and Rajan (1994) report that 28\% of corporations and 45\% of noncorporations in their U.S.A. sample do not have LTD and in the sample collected by Brounen, Jong and Koedik (2005) 25\% of U.K. firms and 29\% of French firms have no LTD at all. Note that the larger proportion of null leverage ratios found in our case may be explained by the larger proportion of SMEs (94.2\%) in our sample and by the fact that, in average, Portuguese LEs are smaller than their U.S.A., U.K. and French counterparts.} \]
Alternatively, as a typical random sample of firms contains many firms that do not use debt, some authors (e.g. Rajan and Zingales 1995 and Bevan and Danbolt 2002) have opted for using a tobit approach for data censored at zero. This model assumes a nonlinear relationship between $Y$ and $X$ given by

$$E(Y|X) = \Phi\left(\frac{X\beta}{\sigma}\right)X\beta + \sigma \phi\left(\frac{X\beta}{\sigma}\right),$$

(2)

where $\Phi(\cdot)$ and $\phi(\cdot)$ denote the standard normal distribution and density functions, respectively, and $\sigma$ is the standard deviation of the error term of the latent linear model that implies (2). However, using the tobit to model leverage ratios suffers also from some drawbacks. First, equation (2), despite being limited from below at zero, still has no upper bound. Second, conceptually, as some authors argue (e.g. Maddala 1991), the latent model underlying (2) is appropriate to describe censored data in the interval $[0,1]$ but its application to data defined only in that interval is not easy to justify: zero leverage ratios are a consequence of individual choices and not of censoring. Finally, the tobit model is very stringent in terms of assumptions: the error term of the latent model has to be homoskedastic and to possess a normal distribution. Using a two-limit variant of tobit, as in Johnson (1997) and Fluck, Holtz-Eakin and Rosen (1998), to take care for both the lower and upper limits of the distribution of leverage ratios would solve only the first issue.

In other areas of financial economics, dependent variables with similar characteristics to leverage ratios are sometimes modelled using the logistic relationship

$$E(Y|X) = \frac{e^{X\beta}}{1 + e^{X\beta}},$$

(3)

which is indeed a natural choice for modelling proportions since it ensures that $0 < E(Y|X) < 1$. However, instead of estimating (3) directly, which would require a nonlinear technique such as nonlinear least squares (NLS), most authors prefer to use LS to estimate the log-odds ratio model defined by

$$E\left(\log\frac{Y}{1-Y} \mid X\right) = X\beta,$$

(4)

which basically corresponds to the linearization of the equation that results from solving $Y = e^{X\beta} / (1 + e^{X\beta})$ in order to $X\beta$. Again, a regression model defined by (4) is not adequate to explain leverage ratios because the transformed dependent variable is not well defined for the boundary values 0 and 1 of $Y$, requiring ad hoc adjustments (such as adding an arbitrarily chosen small constant to all observations of $Y$). Moreover, from (4) it would be very difficult to recover $E(Y|X)$ and, thus,
interpret the model parameters in terms of the leverage ratio, which would still be our main interest.

4.2 Fractional regression model

As the correct specification of the conditional mean of $Y$ is a crucial assumption for the validity of any regression model, the evidence found in papers assuming (1), (2) or (4) may be incorrect (to the best of our knowledge, in no case was that assumption tested) and needs to be validated using suitable econometric models. One of such models is the fractional regression model (FRM) developed by Papke and Wooldridge (1996) to deal with dependent variables defined on the closed interval $[0,1]$. In their model, they assume a functional form for $Y$ that imposes the desired constraints on the values of the dependent variable:

$$E(Y|X) = G(X\beta),$$

(5)

where $G(\cdot)$ is a known nonlinear function satisfying $0 < G(\cdot) < 1$. Papke and Wooldridge (1996) suggest as possible specifications for $G(\cdot)$ any cumulative distribution function. Therefore, the logistic function (3) is a possible choice for $G(\cdot)$. However, instead of being first linearized as discussed above, the model defined by (5) is now estimated directly using nonlinear techniques.

Papke and Wooldridge (1996) showed that, although consistent estimators for $\beta$ could be obtained by estimating (5) by NLS, it is more efficient to assume a Bernoulli distribution for $Y$ conditional on $X$ and estimate the parameters $\beta$ in (5) by maximizing the quasi-likelihood function:

$$LL(\beta) = y \log [G(X\beta)] + (1 - y) \log [1 - G(X\beta)].$$

(6)

Indeed, as the Bernoulli distribution is a member of the linear exponential family, the resulting quasi-maximum likelihood (QML) estimator for $\beta$ will always be consistent, regardless of the true distribution of $Y$ conditional on $X$, provided that (5) is indeed correctly specified (see Gourieroux, Monfort and Trognon 1984 for details). Actually, as in no circumstances can the Bernoulli be the true conditional distribution of leverage ratios, robust standard errors have to be used. In this paper we compute them by applying Papke and Wooldridge’s (1996) equation 9, which merely assumes (5). Thus, similarly to the three regression models discussed in the previous section, the crucial assumption of the FRM is the correct formalization of $E(Y|X)$, which can be tested using the extension of the RESET test outlined in Papke and Wooldridge

4.3 Two-part fractional regression model

Although the FRM (5) may be used to explain the behaviour of a dependent variable characterized by a large number of zero values, theoretically, as discussed in section 3.3, it may be preferable to construct separate models to explain the decisions: (i) to issue or not to issue debt; and (ii) (for those firms that do decide to use debt) on how much debt to issue. Indeed, given that zero leverage ratios occur with too large a frequency than seems to be consistent with a simple model, the factors that explain the former decision may be not the same as those that affect the latter decision or their effect may be different. Therefore, in this section we extend Papke and Wooldridge’s (1996) FRM and develop a two-part FRM (2P-FRM) that mirrors this two-part decision process.\(^{10}\)

The first part of our 2P-FRM governs participation, i.e. specifies a binary outcome model to explain the probability of a firm choosing to use LTD or not. Define

\[
Y^* = \begin{cases} 
0 & \text{for } Y = 0 \\
1 & \text{for } Y \in (0, 1] 
\end{cases} \quad (7)
\]

Then,

\[
\Pr (Y^* = 1 | X) = \Pr (Y \in (0, 1] | X) = F (X \theta) , \quad (8)
\]

where \( \theta \) is a vector of variable coefficients and \( F (\cdot) \) is the cumulative logistic or normal distribution function. The resulting logit or probit model may be estimated, as usual, by ML using the whole sample.

The second part of the 2P-FRM governs positive choices, i.e. the magnitude of nonzero leverage ratios. In this case, a \( G (\cdot) \) function similar to the one defined above for the FRM is also a valid specification:

\[
E (Y | X, Y \in (0, 1]) = G (X \gamma) . \quad (9)
\]

As for the simple FRM, \( G (X \gamma) \) may be estimated by QML but now using only data for firms with positive leverage ratios.

Noting that \( E (Y | X) \) may be decomposed as

\[
E (Y | X) = E (Y | X, Y = 0) \cdot \Pr (Y = 0 | X) + E (Y | X, Y \in (0, 1]) \cdot \Pr (Y \in (0, 1] | X) ,
\]

\(^{10}\)Two-part (or hurdle) models are relatively common in the econometric literature of count data; see Mulhahy (1986) for a seminal paper.
and that the first term on the right-hand side of this expression is identically zero, the 2P-FRM may be described simply by

\[
E(Y|X) = E(Y|X, Y \in (0, 1]) \cdot \Pr(Y \in (0, 1]|X)
\]
\[
= G(X\gamma) \cdot F(X\theta),
\]

(10)

where their two components are to be estimated separately. As \(\gamma\) and \(\theta\) are not required to be the same, this 2P-FRM allows the explanatory variables to influence in independent ways the firm’s choice of using or not LTD and the firm’s choice of LTD level, as Table 1 revealed that should be the case of Portuguese firms. Moreover, comparing (5) and (10) shows that if the mechanisms governing both decisions are indeed different, the functional form of the conditional mean will be affected. Hence, neglecting the special nature of the zero leverage ratios is likely to produce serious misspecification and leads to results that are of little use: the parameters \(\beta\) appearing in (5) are a mixture of the parameters \(\gamma\) and \(\theta\) in (10) and have no clear interpretation.

The crucial assumption for estimating both \(\gamma\) and \(\theta\) consistently is again the correct formalization of \(E(Y|X)\) which, in turn, requires that both \(E(Y|X, Y \in (0, 1])\) and \(\Pr(Y^* = 1|X)\) are properly specified. In this paper we assume a logistic specification for both functions, that is:

\[
E(Y|X) = \frac{e^{X(\gamma + \theta)}}{(1 + e^{X\gamma})(1 + e^{X\theta})},
\]

(11)

To test the assumption made for \(G(X\gamma)\) we apply the same RESET test referred to above, while to test the specification adopted for \(F(X\theta)\) we use Pagan and Vella’s (1989) version of the RESET test and Davidson and MacKinnon’s (1984) heteroskedasticity test. In the former case we do not need to test for heteroskedasticity since regression models for continuously measured proportions with a finite number of boundary observations are always heteroskedastic and the estimation method adopted, QML, has that into account.

11 Recently, Cook, Kieschnick and McCullough (2004) used also a two-part model to explain capital structure choices. Their approach is similar to ours but differ in two important aspects. First, in the second part of the model, they assume a beta distribution for the conditional distribution of (the positive values of) \(Y\) given \(X\) and then estimate the parameters \(\gamma\) by ML. As the beta distribution is not a member of the linear exponential family, in addition to the correct specification of \(E(Y|X, Y \in (0, 1])\) and \(\Pr(Y^* = 1|X)\) required by our model, in their case it is also essential that the true distribution of \(Y\) conditional on \(X\) is indeed the beta distribution. Second, while we opted for using a two-part model in order to be able to test a specific hypothesis about capital structure choices, they were forced to do so: the beta distribution can only be applied to observations on the open interval (0,1).

12 In the former case we do not need to test for heteroskedasticity since regression models for continuously measured proportions with a finite number of boundary observations are always heteroskedastic and the estimation method adopted, QML, has that into account.
FRM can be used to estimate the effect of a change in the explanatory variable \( X_j \) on both the probability of using LTD,

\[
\frac{\partial \Pr (Y^* = 1 | X)}{\partial X_j} = \theta_j \frac{e^{X\theta}}{(1 + e^{X\theta})^2}
\]  

and, if the firm already uses LTD, on the amount utilized:

\[
\frac{\partial E (Y|X, Y \in (0,1])}{\partial X_j} = \gamma_j \frac{e^{X\gamma}}{(1 + e^{X\gamma})^2}.
\]

Moreover, from (10) or (11), we can also calculate the effect of a change in \( X_j \) on the LTD used by all firms:

\[
\frac{\partial E (Y|X)}{\partial X_j} = \frac{\partial G (X\gamma)}{\partial X_j} F (X\theta) + G (X\gamma) \frac{\partial F (X\theta)}{\partial X_j}
\]

\[
= \gamma_j \frac{e^{X\gamma}}{(1 + e^{X\gamma})^2} + \theta_j \frac{e^{X\theta}}{(1 + e^{X\theta})^2} e^{X\gamma} + \theta_j \frac{e^{X\theta}}{(1 + e^{X\theta})^2} e^{X\gamma} + \theta_j \frac{e^{X\theta}}{(1 + e^{X\theta})^2} e^{X\gamma}.
\]

Thus, the total change in LTD can be disaggregated in two parts: (i) the change in LTD of those that already use LTD, weighted by the probability of issuing debt; and (ii) the change in probability of using LTD, weighted by the expected value of LTD among those that already use LTD. This decomposition is similar to that found by McDonald and Moffitt (1980) for the tobit model.

5 Empirical results

5.1 Main findings

In Table 4 we report the empirical results obtained from the estimation of the two models implied by the 2P-FRM. Considering first the empirical adequacy of both models, it seems that they fit the data relatively well in all cases. Indeed, the RESET test provides no evidence of functional form misspecification; for the binary model, Davidson and MacKinnon’s (1984) test for the null hypothesis of homoskedasticity is not significant; and the values found for the pseudo \( R^2 \), although low, are usual in cross-sectional studies.

Table 4 about here

Relative to the decision of issuing debt or not, the estimates obtained for the binary choice model indicate that the only variables which significantly influence
that decision for all the four group of firms are PROFITAB and LIQUIDITY. In all cases, the higher the profitability and the amount of liquid reserves of the firm, the less its probability of using LTD. Clearly, as implied by the pecking-order theory and in opposition to the other two capital structure theories considered in this paper, all types of firms seem to prefer internal resources to external ones to finance their activity.

On the other hand, as predicted by the three theories, we find positive relationships between the resort to LTD and the explanatory variables COLLATERAL and SIZE, which are significant for most groups. Interestingly, the only group where COLLATERAL does not affect significantly the probability of firms raising debt is that of micro firms. In contrast, only for micro firms is the variable AGE important to explain that probability. Therefore, as, on average, micro firms have no or low collateral, it seems that lenders use AGE as a substitute for COLLATERAL when deciding to finance or not the activity of micro firms: older micro firms are more prone to use LTD because they have better access to the debt market since their longer history of survival leads lenders to trust them more, as predicted by the agency costs theory. Indeed, as argued by Berger and Udell (1995), small firms with longer banking relationships pay lower interest rates and are less likely to pledge collateral.

Finally, we find a statistically significant positive effect of GROWTH on the probability of medium and large firms using LTD, which, again, is in line with the pecking-order theory and in opposition to the other two theories. With regard to NDTS, contrary to the trade-off theory, in no case did we find a significant correlation between this variable and the probability of using LTD.

Considering now the results of the second part of our model, which are based only on the firms that do use LTD, we find that, as predicted by the pecking-order theory: (i) both PROFITAB and LIQUIDITY are negatively related to the amount of LTD issued, although only the effect of the former variable is significant; (ii) GROWTH has a positive relationship with LTD, which is significant for small and large firms; and (iii) AGE affects negatively the proportion of LTD used in the financing of the activity of micro and small firms. Interestingly, note the opposite effects that AGE has over the two levels of the model estimated for micro firms: on the one hand, older firms are more prone to use LTD, for the reasons explained above; on the other hand, conditional upon the decision to issue debt, they use a lower proportion of LTD in the financing of their businesses than younger firms. A possible reason for the latter effect is the accumulation of retained earnings over time by micro firms that are successful enough to survive for a long time, as suggested (in
general) by the pecking-order theory. Indeed, part of those retained earnings may be used to repurchase some debt, which in the case of micro firms often comes from family and friends of their owners.

Also in contrast to the results obtained for the first part of our 2P-FRM, we find that both \textit{COLLATERAL} and \textit{SIZE} are either not related or have a negative impact on the relative amount of LTD used by SMEs. Although these results may seem somewhat surprising, note that they are not in contradiction to the positive relationships predicted by all the capital structure theories and confirmed by almost all previous empirical studies. Indeed, as discussed later (see the last two paragraphs of this section), the aggregate effect of both \textit{COLLATERAL} and \textit{SIZE} on the unconditional amount of LTD used by firms, which is the only one that was estimated by prior studies, is also clearly positive according to our model (except, in the case of \textit{COLLATERAL}, for micro firms, which are usually ignored by empirical studies). What our results show is that, in the case of SMEs, the positive effect of \textit{COLLATERAL} and \textit{SIZE} is exercised mainly over the probability of a firm issuing LTD. Once the firm decide and is able to raise LTD, that positive impact disappears, probably because, in relative terms, smaller firms need more debt financing to expand their activities since their access to external equity is more limited.

Finally, only for large firms does \textit{NDTS} seem to be an important determinant of the capital structure, maybe because large firms have generally higher marginal tax rates than smaller firms and, therefore, more tax deduction benefit of (debt and) non-debt tax shields. Moreover, in general, due to poor management skills, smaller firms may not be aware of such benefits.

Overall, the results reported in table 4 suggest that the determinants of LTD for micro, small, medium and large firms differ in some aspects. For example, we find that \textit{AGE} is an important determinant of the capital structure of micro firms, while \textit{NDTS} is important only for large firms. Even when the type of relationship (positive/negative) is the same for all groups, it seems that there are important differences in the magnitude of the coefficients in some cases. To formally test the hypothesis whether the same regression model describes in an appropriate way the capital structure choices for all size-based group of firms, we applied the Chow-type tests described in the Appendix. In Table 5 we report the \textit{p}-values estimated for both parts of the model for the null hypothesis of no significant differences between all the coefficients relative to each pair of size-based groups of firms.

\textbf{Table 5 about here}
For the binary choice model, we find significant differences between most groups of firms, the only exception being relative to medium and large firms. For the fractional regression model, the differences are attenuated since they are significant only when relative to micro versus medium or large firms and to small versus large firms. Overall, our results suggest that when analyzing capital structure choices, three distinct size-based groups of firms should be considered (assuming that the European Commission definitions are used): (i) micro firms; (ii) small firms; and (iii) medium/large firms. Indeed, in no case did we reject the hypothesis of equality of the coefficients for the medium and large groups of firms, i.e. the determinants of the financing decisions of medium firms seem to be more similar to those of large firms than those of the other SMEs. This similarity between medium and large firms may be the reason why many of the previous studies on capital structures did not find significant differences between the financing decisions of SMEs and LEs: according to our results, the inclusion of medium-sized firms in the SME group is likely to diminish substantially the differences between SMEs and LEs in terms of capital structure choice.

The results reported in Table 4 also suggest that, as assumed in this paper, the main determinants of the probability of a firm using LTD are not exactly the same as those of the amount of LTD used. Indeed, as LIQUIDITY is important only for the former decision and, for some groups, COLLATERAL, SIZE and AGE affect in opposite ways each decision, it seems that a two-part model such as the 2P-FRM that we employed is in fact a better option for explaining the capital structure of firms than standard one-part models. However, based exclusively on the coefficients reported in Table 4, we cannot know which is the overall effect of each variable on the proportion of LTD used by firms, especially for the variables that have opposite effects on the two parts of the model. For example, do micro firms with higher collateral use more or less LTD on average? To answer this question, in Table 6 we report the partial effects estimated for each variable, which are the averages of the partial effects calculated for each individual. We report three different partial effects: (i) the effect on the probability of using LTD ($\Delta P_1$), which was defined in (12); (ii) the effect on the proportion of LTD used by firms that already use LTD ($\Delta E_1$) defined in (13); and (iii) the effect on the proportion of LTD used by all firms ($\Delta E$) defined in (15). It is this last effect that gives the combined effect of each variable on the unconditional proportion of LTD used by firms.

Table 6 about here

The total partial effects reported in the column labelled $\Delta E$ show that, overall, NDT$S$, PROFITAB and LIQUIDITY affect negatively the proportion of LTD
used by firms, $SIZE$ and $GROWTH$ influence it positively, and the effect of $AGE$ is approximately nil in all cases. For micro firms the overall effect of $COLLATERAL$ is negative, while for the other size-based groups it is positive. Clearly, given the signs found for $PROFITAB$, $LIQUIDITY$ and $GROWTH$, the pecking-order theory seems to be the one that best describes the capital structure of firms, as already suggested above.

The total effect found for $AGE$ in the micro firms case illustrates clearly one of the most important advantages of the 2P-FRM. Indeed, it was noted above that, in the case of micro firms, $AGE$ had conflicting but significant impacts on the two levels of the model proposed here. A single one-part model would fail to recognize the existence of these different levels, estimating just the aggregate effect of $AGE$, and, hence, would conclude incorrectly that this variable has no impact on LTD. In fact, for micro firms, for each additional year of existence, their probability of raising LTD increases about 0.3 percentage points, while the percentage of LTD used by firms that already use it as a financing source decreases about 0.4 percentage points. One-part models would also fail to recognize the distinct impacts of $COLLATERAL$ and $SIZE$ on each decision found for some groups of firms.

### 5.2 Comparison with alternative models

In Table 7 we report the results obtained by considering two other formulations for the capital structure decisions of firms: the simple linear model considered by most of the previous papers and a standard FRM that uses all observations to estimate a single equation. As expected, the linear model is not at all adequate for modelling capital structure choices. Indeed, the RESET test rejects the hypothesis of correct functional form specification in three out of four cases and the estimated models originate predictions outside the unit interval for all groups. In contrast, only in one case (and only at the 10% level) the RESET test indicates that the functional form used by the FRM is misspecified. This was also expected since, as we said before, from an econometric point of view, the FRM is appropriate to deal with fractional dependent variables characterized by a large number of zeros. The main disadvantage of the FRM is that identified above: using this model, it is impossible to quantify the different, sometimes conflicting, impacts that each explanatory variable has on the two sequential capital structure decisions made by firms.

Table 7 about here

Despite the clear inappropriateness of the linear model, note that, in terms of the significance of the variables, very similar conclusions are achieved for both one-part
models. To be able to compare these results with those obtained for the 2P-FRM, in Table 8 we report again the total partial effects computed before for the 2P-FRM and present also those calculated for the linear model (which assumes that they are constant for all individuals and, hence, are simply given by the estimated coefficients) and for the FRM (which were calculated using an expression similar to (13) but based on the full sample and on the FRM estimates for $\beta$). In all cases the estimated sign of the relationship between each explanatory variable and the proportion of LTD used by firms is the same for all models. In most cases the magnitude of the estimated effects for each model is not very different except for the group of micro firms, where the linear model underestimates substantially the effect of many variables. Note that this is precisely the case where linear models are expected to be more inadequate since the number of firms with no LTD is very large.

Table 8 about here

6 Conclusion

In this paper we study the leverage decisions of Portuguese firms in order to test the following two hypotheses about which traditional theories of capital structure do not provide clear answers: (i) the determinants of capital structure are different for micro, small, medium and large firms; and (ii) the factors that determine whether or not a firm issues debt are different from those that determine how much debt it issues. To be able to test the second hypothesis, we developed a 2P-FRM, which can be used to determine both changes in the probability of using LTD and changes in the proportion of LTD used by firms that already use it. The former changes are estimated using a binary choice model, while for the latter we use a fractional regression model that takes into account the bounded nature of leverage ratios. The results obtained with the proposed model are quite encouraging since all the econometric tests applied provided no evidence of any type of model misspecification.

We found strong support for both hypotheses. On the one hand, for the four different size-based groups of firms considered in the paper we found differences in terms of magnitude, direction and significance of some regression coefficients of the different capital structure determinants. Nevertheless, the effects on leverage found for PROFITABILITY (-), LIQUIDITY (-) and GROWTH (+) suggest that the pecking-order theory may be more suitable to describe the capital structure choices made by all size-based groups of firms. On the other hand, our empirical results show that some variables may have opposite effects on the two levels of the model
and that ignoring these differences may lead to erroneous conclusions. One of the most interesting results of the paper is that older micro firms are more prone to use LTD: due to the low collateral of micro firms, lenders seem to use the firm’s age (i.e. reputation) as a substitute for collateral. This result is in line with Berger and Udell’s (1995) findings that, in the case of SMEs, older firms (with, presumably, longer banking relationships) pay lower interest rates and are less likely to pledge collateral.

7 Appendix: Chow-type statistics for testing for differences in regression functions across groups

In linear models, it is usual to apply the Chow statistic to test whether the same regression model describes correctly the dependent variable for two specific groups of individuals. In such a case, this test may be implemented as a simple $F$ test for the null hypothesis $H_0 : \delta = 0$, where $\delta$ is the vector of parameters associated with the interaction terms $d \cdot X$ of the equation

$$E (Y | X) = X\beta + (d \cdot X) \delta,$$

where $d$ is a dummy variable which takes on the value one for one group (e.g. micro firms) and the value zero for other group (e.g. small firms). Under the null hypothesis there are no significant differences between the two groups and the same regression model may be used for both groups.

The extension of this test for the binary choice model of the 2P-FRM is straightforward since that model is estimated by ML. In addition to the model defined in (8), $Pr (Y^* = 1 | X) = F (X\theta)$, we simply have to estimate the augmented model

$$Pr (Y^* = 1 | X) = F [X\theta + (d \cdot X) \delta]$$

and apply a conventional likelihood-ratio test for $H_0 : \delta = 0$.

Similarly, for the FRM defined in (9), $E (Y | X, Y \in (0, 1]) = G (X\gamma)$, the alternative model is given by:

$$E (Y | X, Y \in (0, 1]) = G [X\gamma + (d \cdot X) \delta].$$

However, as the model is estimated by QML and we have to use robust estimation of the covariance matrix, a Chow-type test constructed along the lines of the robust RESET test outlined in Papke and Wooldridge (1996) has to be used. See also

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Table 1: Sample statistics

<table>
<thead>
<tr>
<th>A. Distribution of sample by firm size</th>
<th>Micro</th>
<th>Small</th>
<th>Medium</th>
<th>Large</th>
<th>Total</th>
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<tbody>
<tr>
<td>#</td>
<td>1446</td>
<td>1951</td>
<td>1024</td>
<td>271</td>
<td>4692</td>
</tr>
<tr>
<td>%</td>
<td>30.8</td>
<td>41.6</td>
<td>21.8</td>
<td>5.8</td>
<td>100.0</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>B. Firms with null leverage ratios</th>
<th>#</th>
<th>%</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>#</td>
<td>1282</td>
<td>88.7</td>
<td>1499</td>
<td>76.8</td>
<td>524</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C. Leverage ratios for the whole sample</th>
<th>Mean</th>
<th>Median</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.053</td>
<td>0.000</td>
<td>0.089</td>
<td>0.000</td>
<td>0.147</td>
<td>0.000</td>
<td>0.152</td>
<td>0.050</td>
<td>0.094</td>
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<tr>
<td>Median</td>
<td>0.466</td>
<td>0.432</td>
<td>0.385</td>
<td>0.355</td>
<td>0.302</td>
<td>0.284</td>
<td>0.256</td>
<td>0.242</td>
<td>0.316</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>D. Leverage ratios for firms that use debt</th>
<th>Mean</th>
<th>Median</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.466</td>
<td>0.432</td>
<td>0.385</td>
<td>0.355</td>
<td>0.302</td>
<td>0.284</td>
<td>0.256</td>
<td>0.242</td>
<td>0.316</td>
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Table 2: Explanatory variables

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Name</th>
<th>Proxy</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Non-debt tax shields</td>
<td>NDTS</td>
<td>ratio between depreciation and earnings before interest, taxes and depreciation</td>
<td></td>
</tr>
<tr>
<td>2. Collateral</td>
<td>COLLATERAL</td>
<td>sum of tangible assets and inventories, divided by total assets</td>
<td></td>
</tr>
<tr>
<td>3. Size</td>
<td>SIZE</td>
<td>natural logarithm of sales</td>
<td></td>
</tr>
<tr>
<td>4. Profitability</td>
<td>PROFITAB</td>
<td>ratio between earnings before interest and taxes and total assets</td>
<td></td>
</tr>
<tr>
<td>5. Expected growth</td>
<td>GROWTH</td>
<td>percentage change in total assets</td>
<td></td>
</tr>
<tr>
<td>6. Age</td>
<td>AGE</td>
<td>years since foundation</td>
<td></td>
</tr>
<tr>
<td>7. Liquidity</td>
<td>LIQUIDITY</td>
<td>sum of cash and marketable securities, divided by current assets</td>
<td></td>
</tr>
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Table 3: Summary statistics for the explanatory variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Micro</th>
<th>Small</th>
<th>Medium</th>
<th>Large</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDTS</td>
<td>Mean</td>
<td>0.866</td>
<td>0.802</td>
<td>0.809</td>
<td>0.902</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>0.503</td>
<td>0.576</td>
<td>0.629</td>
<td>0.623</td>
</tr>
<tr>
<td>COLLATERAL</td>
<td>Mean</td>
<td>0.355</td>
<td>0.420</td>
<td>0.466</td>
<td>0.443</td>
</tr>
<tr>
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<td>Median</td>
<td>0.322</td>
<td>0.414</td>
<td>0.474</td>
<td>0.462</td>
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<tr>
<td>PROFITAB</td>
<td>Mean</td>
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<td>0.062</td>
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<td>0.051</td>
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<tr>
<td></td>
<td>Median</td>
<td>0.047</td>
<td>0.047</td>
<td>0.042</td>
<td>0.035</td>
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<td>GROWTH</td>
<td>Mean</td>
<td>17.547</td>
<td>12.979</td>
<td>9.294</td>
<td>7.451</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>6.436</td>
<td>6.637</td>
<td>4.990</td>
<td>5.013</td>
</tr>
<tr>
<td>AGE</td>
<td>Mean</td>
<td>16.172</td>
<td>19.820</td>
<td>27.331</td>
<td>34.203</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>12.000</td>
<td>17.000</td>
<td>22.000</td>
<td>29.000</td>
</tr>
<tr>
<td>LIQUIDITY</td>
<td>Mean</td>
<td>0.296</td>
<td>0.175</td>
<td>0.124</td>
<td>0.107</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>0.192</td>
<td>0.103</td>
<td>0.059</td>
<td>0.053</td>
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Table 4: Regression results

<table>
<thead>
<tr>
<th></th>
<th>Part I: Binary model</th>
<th></th>
<th>Part II: Fractional regression model</th>
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<tbody>
<tr>
<td></td>
<td>Micro</td>
<td>Small</td>
<td>Medium</td>
</tr>
<tr>
<td><strong>NDTS</strong></td>
<td>-0.186</td>
<td>-0.046</td>
<td>-0.069</td>
</tr>
<tr>
<td></td>
<td>(-1.40)</td>
<td>(-1.02)</td>
<td>(-1.27)</td>
</tr>
<tr>
<td><strong>COLLATERAL</strong></td>
<td>0.334</td>
<td>1.273</td>
<td>1.855***</td>
</tr>
<tr>
<td></td>
<td>(0.96)</td>
<td>(4.95)</td>
<td>(5.13)</td>
</tr>
<tr>
<td><strong>SIZE</strong></td>
<td>0.629***</td>
<td>0.426***</td>
<td>0.338***</td>
</tr>
<tr>
<td></td>
<td>(7.48)</td>
<td>(6.95)</td>
<td>(4.39)</td>
</tr>
<tr>
<td><strong>PROFITAB</strong></td>
<td>-3.071***</td>
<td>-4.073***</td>
<td>-5.862***</td>
</tr>
<tr>
<td></td>
<td>(-2.21)</td>
<td>(-4.03)</td>
<td>(-4.84)</td>
</tr>
<tr>
<td><strong>GROWTH</strong></td>
<td>-0.001</td>
<td>0.002</td>
<td>0.009***</td>
</tr>
<tr>
<td></td>
<td>(-0.46)</td>
<td>(0.97)</td>
<td>(2.88)</td>
</tr>
<tr>
<td><strong>AGE</strong></td>
<td>0.017**</td>
<td>0.005</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(2.13)</td>
<td>(1.10)</td>
<td>(-0.02)</td>
</tr>
<tr>
<td><strong>LIQUIDITY</strong></td>
<td>-1.240***</td>
<td>-1.698***</td>
<td>-2.165***</td>
</tr>
<tr>
<td></td>
<td>(-3.00)</td>
<td>(-4.49)</td>
<td>(-4.57)</td>
</tr>
<tr>
<td><strong>CONSTANT</strong></td>
<td>-9.629***</td>
<td>-7.250***</td>
<td>-5.608***</td>
</tr>
<tr>
<td></td>
<td>(-8.49)</td>
<td>(-8.18)</td>
<td>(-4.58)</td>
</tr>
</tbody>
</table>

Number of observations: Micro 1446, Small 951, Medium 1024, Large 271, Micro 164, Small 452, Medium 500, Large 161

Notes: below the coefficients we report t-statistics in parentheses; for the test statistics we report p-values; ***, ** and * denote coefficients or test statistics which are significant at 1%, 5% or 10%, respectively; for the binary model, see McFadden (1974), Pagan and Vella (1989) and Davidson and MacKinnon (1984) for details on, respectively, the pseudo $R^2$ and the RESET and heteroskedasticity tests applied; for the fractional model, the pseudo $R^2$ was calculated as the correlation between the predicted and actual values of LTD, while the RESET test was implemented as described in Papke and Wooldridge (1996).
Table 5: Chow-type statistics (p-values)

<table>
<thead>
<tr>
<th></th>
<th>Part I: Binary model</th>
<th></th>
<th>Part II: Fractional model</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Small</td>
<td>Medium</td>
<td>Large</td>
<td>Small</td>
</tr>
<tr>
<td>Micro</td>
<td>0.008***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.317</td>
</tr>
<tr>
<td>Small</td>
<td>—</td>
<td>0.002***</td>
<td>0.081*</td>
<td>—</td>
</tr>
<tr>
<td>Medium</td>
<td>—</td>
<td>0.694</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

Notes: the Chow-type statistics were calculated as described in the Appendix; ***, **, and * denote test statistics which are significant at 1%, 5% or 10%, respectively.

Table 6: Partial effects for the two-part fractional regression models

<table>
<thead>
<tr>
<th></th>
<th>Micro</th>
<th>Small</th>
<th>Medium</th>
<th>Large</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\Delta P_1$</td>
<td>$\Delta E_1$</td>
<td>$\Delta E$</td>
<td>$\Delta P_1$</td>
</tr>
<tr>
<td><strong>NDTS</strong></td>
<td>-0.030</td>
<td>-0.003</td>
<td>-0.015</td>
<td>-0.007</td>
</tr>
<tr>
<td><strong>COLLATERAL</strong></td>
<td>0.054</td>
<td>-0.212</td>
<td>-0.044</td>
<td>0.203</td>
</tr>
<tr>
<td><strong>SIZE</strong></td>
<td>0.101</td>
<td>0.019</td>
<td>0.053</td>
<td>0.068</td>
</tr>
<tr>
<td><strong>PROFITAB</strong></td>
<td>-0.494</td>
<td>-0.779</td>
<td>-0.477</td>
<td>-0.650</td>
</tr>
<tr>
<td><strong>GROWTH</strong></td>
<td>0.000</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td><strong>AGE</strong></td>
<td>0.003</td>
<td>-0.004</td>
<td>0.000</td>
<td>0.001</td>
</tr>
<tr>
<td><strong>LIQUIDITY</strong></td>
<td>-0.199</td>
<td>-0.107</td>
<td>-0.126</td>
<td>-0.271</td>
</tr>
</tbody>
</table>

Notes: $\Delta P_1$ is the effect on the probability of using long-term debt, $\Delta E_1$ is the effect on the proportion of long-term debt used by firms that already use it, and $\Delta E$ is the effect on the proportion of long-term debt used by any firm; each effect was calculated as the average of the effects computed for each individual using expressions (12), (13) and (15), respectively.
Table 7: Regression results for the linear and fractional regression models

<table>
<thead>
<tr>
<th></th>
<th>Linear model</th>
<th></th>
<th></th>
<th>Fractional regression model</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Micro</td>
<td>Small</td>
<td>Medium</td>
<td>Large</td>
<td>Micro</td>
<td>Small</td>
<td>Medium</td>
</tr>
<tr>
<td>NDTTS</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.005</td>
<td>-0.021***</td>
<td>-0.236</td>
<td>-0.028</td>
<td>-0.079</td>
</tr>
<tr>
<td></td>
<td>(-0.40)</td>
<td>(-1.04)</td>
<td>(-1.41)</td>
<td>(-4.03)</td>
<td>(-0.99)</td>
<td>(-0.90)</td>
<td>(-1.44)</td>
</tr>
<tr>
<td>COLLATERAL</td>
<td>-0.030*</td>
<td>0.038**</td>
<td>0.091***</td>
<td>0.146**</td>
<td>-0.265</td>
<td>0.470*</td>
<td>0.744***</td>
</tr>
<tr>
<td></td>
<td>(-1.66)</td>
<td>(1.78)</td>
<td>(2.64)</td>
<td>(2.02)</td>
<td>(-0.73)</td>
<td>(1.75)</td>
<td>(2.56)</td>
</tr>
<tr>
<td>SIZE</td>
<td>0.028***</td>
<td>0.019***</td>
<td>0.010</td>
<td>0.007</td>
<td>0.574***</td>
<td>0.236**</td>
<td>0.079</td>
</tr>
<tr>
<td></td>
<td>(6.65)</td>
<td>(4.13)</td>
<td>(1.47)</td>
<td>(0.62)</td>
<td>(6.95)</td>
<td>(4.13)</td>
<td>(1.38)</td>
</tr>
<tr>
<td>PROFITAB</td>
<td>-0.068***</td>
<td>-0.232***</td>
<td>-0.457***</td>
<td>-0.638***</td>
<td>-4.620***</td>
<td>-4.153***</td>
<td>-5.642***</td>
</tr>
<tr>
<td></td>
<td>(-2.76)</td>
<td>(-5.23)</td>
<td>(-5.28)</td>
<td>(-4.36)</td>
<td>(-2.57)</td>
<td>(-4.56)</td>
<td>(-5.92)</td>
</tr>
<tr>
<td>GROWTH</td>
<td>0.000</td>
<td>0.000*</td>
<td>0.001**</td>
<td>0.002**</td>
<td>0.000</td>
<td>0.004*</td>
<td>0.007***</td>
</tr>
<tr>
<td></td>
<td>(-0.01)</td>
<td>(1.75)</td>
<td>(2.55)</td>
<td>(2.38)</td>
<td>(-0.22)</td>
<td>(1.89)</td>
<td>(3.17)</td>
</tr>
<tr>
<td>AGE</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.008</td>
<td>-0.004</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(1.04)</td>
<td>(-0.81)</td>
<td>(-0.43)</td>
<td>(0.83)</td>
<td>(0.87)</td>
<td>(-0.86)</td>
<td>(-0.31)</td>
</tr>
<tr>
<td>LIQUIDITY</td>
<td>-0.047***</td>
<td>-0.094***</td>
<td>-0.173***</td>
<td>-0.120</td>
<td>-1.388***</td>
<td>-1.644***</td>
<td>-1.872***</td>
</tr>
<tr>
<td></td>
<td>(-3.93)</td>
<td>(-4.20)</td>
<td>(-4.75)</td>
<td>(-1.24)</td>
<td>(-3.20)</td>
<td>(-3.51)</td>
<td>(-4.00)</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>-0.261***</td>
<td>-0.150**</td>
<td>-0.004</td>
<td>0.008</td>
<td>-9.338***</td>
<td>5.297***</td>
<td>-2.860***</td>
</tr>
<tr>
<td></td>
<td>(-5.29)</td>
<td>(-2.34)</td>
<td>(-0.04)</td>
<td>(0.04)</td>
<td>(-8.10)</td>
<td>(6.26)</td>
<td>(-3.18)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>1446</td>
<td>1951</td>
<td>1024</td>
<td>271</td>
<td>1446</td>
<td>1951</td>
<td>1024</td>
</tr>
<tr>
<td>RESET test</td>
<td>0.000***</td>
<td>0.084*</td>
<td>0.036**</td>
<td>0.603</td>
<td>0.321</td>
<td>0.094*</td>
<td>0.355</td>
</tr>
<tr>
<td>% of predictions outside the unit interval</td>
<td>9.61</td>
<td>2.31</td>
<td>1.46</td>
<td>2.58</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

Notes: below the coefficients we report t-statistics in parentheses; for the test statistics we report p-values; ***, ** and * denote coefficients or test statistics which are significant at 1%, 5% or 10%, respectively; the RESET test applied to the linear and fractional models was implemented as described in Ramsey (1969) and Papke and Wooldridge (1996), respectively.
Table 8: Total partial effects

<table>
<thead>
<tr>
<th></th>
<th>LS</th>
<th>FRM</th>
<th>2P-FRM</th>
<th>LS</th>
<th>FRM</th>
<th>2P-FRM</th>
<th>LS</th>
<th>FRM</th>
<th>2P-FRM</th>
<th>LS</th>
<th>FRM</th>
<th>2P-FRM</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDTS</td>
<td>-0.002</td>
<td>-0.027</td>
<td>-0.015</td>
<td>-0.001</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.005</td>
<td>-0.008</td>
<td>-0.009</td>
<td>-0.021</td>
<td>-0.029</td>
<td>-0.025</td>
</tr>
<tr>
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<td>-0.030</td>
<td>-0.030</td>
<td>-0.044</td>
<td>0.038</td>
<td>0.039</td>
<td>0.028</td>
<td>0.091</td>
<td>0.076</td>
<td>0.094</td>
<td>0.146</td>
<td>0.119</td>
<td>0.130</td>
</tr>
<tr>
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<td>0.065</td>
<td>0.053</td>
<td>0.019</td>
<td>0.020</td>
<td>0.015</td>
<td>0.010</td>
<td>0.008</td>
<td>0.010</td>
<td>0.007</td>
<td>0.007</td>
<td>0.006</td>
</tr>
<tr>
<td>PROFITAB</td>
<td>-0.068</td>
<td>-0.523</td>
<td>-0.477</td>
<td>-0.232</td>
<td>-0.343</td>
<td>-0.318</td>
<td>-0.457</td>
<td>-0.579</td>
<td>-0.592</td>
<td>-0.638</td>
<td>-0.720</td>
<td>-0.748</td>
</tr>
<tr>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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<tr>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>LIQUIDITY</td>
<td>-0.047</td>
<td>-0.157</td>
<td>-0.126</td>
<td>-0.094</td>
<td>-0.136</td>
<td>-0.119</td>
<td>-0.173</td>
<td>-0.192</td>
<td>-0.173</td>
<td>-0.120</td>
<td>-0.117</td>
<td>-0.191</td>
</tr>
</tbody>
</table>