UNIVERSIDADE DE ÉVORA

ESCOLA DE CIÊNCIAS E TECNOLOGIA

DEPARTAMENTO DE MATEMÁTICA

Using fractional regression models to analyse the determinants of capital structure and efficiency of European manufacturing firms.

Bhaswar Chakma

Orientação: Joaquim José dos Santos Ramalho

Jorge Manuel Azevedo Santos

Mestrado em Modelação Estatística e Análise de Dados

Dissertação

Évora, 2017

Aplicação de modelos de regressão para dados fraccionários à análise dos determinantes da estrutura de capital e eficiência de empresas industriais Europeias

Resumo

Quando a variável dependente num modelo econométrico tem uma natureza fraccionária, correspondendo a uma proporção ou taxa, o modelo de regressão linear não é a forma mais indicada de modelar essa variável. Em vez disso, deve usar-se o chamado modelo de regressão para dados fraccionários, o qual tem em conta a natureza proporcional e limitada da variável dependente. Esta dissertação descreve as principais características deste modelo e realiza dois estudos empiríços que ilustram a sua utilidade na área da Economia e Finanças. O primeiro estudo analisa a estrutura de capital de empresas transformadoras de Portugal, Grécia, França e Alemanha usando dados para os anos de 2007 e 2013. O objectivo principal é analisar como é que a recente crise financeira, o tipo de tecnologia utilizada (High-Tech ou Low-Tech) e a dimensão das empresas (PME ou Grande) afectam os seus níveis de endividamento. Os resultados mostram que as empresas High-Tech recorrem menos a dívida, que a crise financeira afectou de forma significativa as decisões de financiamento das empresas e que as PME passaram a usar menos dívida desde o início da crise. O segundo estudo analiza os scores de eficiência das mesmas empresas, compreendendo duas etapas. Na primeira, a metodologia de Data Envelopment Analysis (DEA) é usada para obter os scores de eficiência. Na segunda etapa, os modelos de regressão fraccionários são usados para analisar esses scores. Os principais objectivos do segundo estudo são verificar como é que a crise financeira, o tipo de tecnologia, a dimensão e o país de origem afectam a eficiência das empresas. Os resultados mostram que os dois primeiros factores não influenciam a eficiência, que as grandes empresas são mais eficientes que as PME e que as empresas Gregas são menos eficientes.

Palavras-chave: Modelos de regressão fraccionários; Estrutura de capital; Endividamento; Crise financeira; DEA

Using fractional regression models to analyse the determinants of capital structure and efficiency of European manufacturing firms

Master Thesis Presented to the
Department of Mathematics at the
University of Évora

In Partial Fulfillment of the Requirements for the Degree of
Master in Statistical Modeling and Data Analysis

Main Supervisor: Joaquim José dos Santos Ramalho
Full Professor, Department of Economics, Instituto Universitário de Lisboa

Co-Supervisor: Jorge Manuel Azevedo Santos
Assistant Professor, Department of Mathematics, University of Évora

Submitted in 2017 by:
Bhaswar Chakma
ID: M36653

Abstract

Fractional regression models are effective when the variable of interest appears in the form of proportion or fraction or rate. In other words, use of fractional regression models becomes appropriate when the dependent variable is defined only on the standard unit interval. This thesis surveys fractional regression models, and conducts two studies using these models. The first study analyses capital structure of manufacturing firms of Portugal, Greece, France, and Germany by using data from the years 2007 and 2013. It primarily tries to find how financial crisis, use of technology (High-Tech or Low-Tech), and firm size (SME or large) affect firms' capital structure decisions. Results show that firms that use high technology comparatively take less debts, financial crisis affects capital structure decisions significantly, and SMEs take less debt after crisis. The second study analyses efficiency scores of firms using the same dataset. It has two stages. The first stage uses data envelopment analysis (DEA) to obtain efficiency scores. Then the second stage employs fractional regression models to analyse those scores. The main aims of the second study are to find how financial crisis, use of technology, firm size (SME or large), and country of origin affect efficiency of firms. Results provide evidence that financial crisis does not affect efficiency of firms, use of technology does not play any role in explaining efficiency of firms, large firms more efficient than SMEs, and firms in Greece are comparatively less efficient.

Keywords Fractional regression models; Capital structure; Financial leverage; Financial crisis; Second-stage DEA

JEL Classification C12; C13; C25; C51; G01; G31

To my wife, Nancy. If she had not taught me mathematics, I would not have come this far.

Acknowledgements

First of all, I would like to express my sincere gratitude to Prof. Joaquim José dos Santos Ramalho, who, notwithstanding the fact that I had a smattering of econometrics, agreed to become my main supervisor. He continuously provided me guidance with great patience, and meticulously checked my work. Without any exaggeration, I am lucky to have him as my mentor and supervisor. I would also like to thank my co-supervisor Prof. Jorge Manuel Azevedo Santos, who guided me in an amiable manner. Last but not least, I would like to thank my scholarship coordinators Prof. José Carlos Brandão Tiago Oliveira and Prof. Imme Pieter van Den Berg. Without their generous consideration, I would not have been able to pursue my studies at University of Évora.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Fractional regression is comparatively a new tool in econometrics. Econometricians employ fractional regression models when the variable of interest appears in the form of proportion or fraction or rate. More precisely, use of fractional regression models becomes germane when the dependent variable ranges between 0 and 1. Possible intervals for such dependent variable are [0,1], (0,1), (0,1], and [0,1). In economics, variable of interest often appears in such settings. Examples include Gini coefficient (inequality measures), proportion of debt in the financial mix of firms, and efficiency scores, to name a few. Before the introduction of fractional regression models, researchers primarily used linear models to study how a set of explanatory variables influences a given fractional response variable. This approach, however, is not appropriate because linear models do not guarantee that the predicted values of the dependent variable will lie within the desired interval. By contrast, fractional regression models are efficacious in restricting the predicted values of the dependent variable within its actual interval.

Jeffrey Wooldridge and Leslie Papke, professors of economics at Michigan State University, first introduced fractional regression models in a seminal paper in 1996. In that paper, they studied participation rates of employees in firms' 401(k) retired plans by employing fractional regression models. Since then, these models have been applied in numerous studies consisting various topics. For example, to evaluate an education policy, Papke and Wooldridge (1996) studied the pass rates for an exam administered to fourth grade Michigan students over time, and J. J. S. Ramalho and Silva (2009) studied financial leverage decisions of micro, small, medium, and large firms. The fractional regression models are either based on maximum likelihood(ML) method or quasi-maximum likelihood(QML) method. In fact, ML based models can only be used when the dependent variable does not contain 0s or 1s i.e. (0,1). By contrast, QML estimators work on any possible interval of the fractional dependent variable.

This thesis surveys fractional regression models, and presents two applications of these models. To be specific, Chapter 2 of this thesis delineates fractional regression. In the first section, it explains why other regression models are inappropriate given a fractional dependent variable. Then, in the second section, it presents maximum likelihood and quasi-maximum likelihood methods, which are inevitable in explaining fractional regression models, in great details. Finally, the last section of Chapter 2 presents fractional regression models. Following the discussion of fractional regression models, Chapter 3 and Chapter 4 of this thesis present two applications of these models using financial data of European manufacturing firms which either use high technology or low technology from the years 2007 and 2013. In fact, Chapter 3 presents a study on capital structure of firms, where the variable of interest is a proportion of debt. And Chapter 4 presents a study on efficiency of firms. In doing so, it first employs data envelopment analysis to obtain efficiency scores, and then uses fractional regression models to study how those scores vary given some exogenous variables.

Chapter 2

Econometric Methodology

This chapter begins with a brief discussion on the inability of standard regression models to model a fractional response variable from a methodological perspective. Then follows a detailed discussion on maximum likelihood and quasi-maximum likelihood, which are building blocks of modeling fractional response variables. Finally, the last section presents a discussion of fractional regression models.

2.1 Standard Regression Models

Before the introduction of fractional regression models by Papke and Wooldridge (1996), there were mainly three approaches to model fractional response variables. To describe these approaches suppose that the fractional variable of interest is y such that $0 \leq y \leq 1$. Let $\mathbf{x}$ be a vector of k covariates and $\boldsymbol{\theta}$ be the vector of parameters to be estimated. Furthermore, let $f(\mathbf{y}|\mathbf{x}, \boldsymbol{\theta})$ denote the conditional density of y, which may be known or unknown.

The first approach was to use linear models such as the Ordinary Least Squares(OLS). This approach simply ignores the bounded nature of y and assumes a linear conditional mean for y:

$$E(y|\mathbf{x}) = \mathbf{X}\boldsymbol{\theta}$$

Linear models estimate a constant partial effect for the explanatory variable. However, y is strictly bounded from above and below. It is unlikely that the effect of any explanatory variable is constant throughout its entire range. Hence, constant partial effects generated by linear models are incompatible with the boundness of the dependent variable. Moreover, unless necessary adjustments are made, a linear specification cannot guarantee that predicted values of y lie between 0 and 1.

Some researchers, considering the flaws of the first approach, opted for a logistic relationship:

$$E(y|\mathbf{x}) = \frac{e^{\mathbf{X}\boldsymbol{\theta}}}{1 + e^{\mathbf{X}\boldsymbol{\theta}}}.$$

This relationship is, of course, a natural choice for modeling fractional response variables since it ensures that $0 \leq E(y|x) \leq 1$. However, because it requires nonlinear techniques, most researchers, rather than estimating the equation directly, used to choose OLS to estimate the selected log-odds ratio model:

$$E(log\frac{y}{1-y}|\mathbf{x}) = \mathbf{X}\boldsymbol{\theta}.$$

This equation corresponds to the linearization of the equation that results from solving $y = \frac{e^{(\mathbf{X}\boldsymbol{\theta})}}{1+e^{(\mathbf{X}\boldsymbol{\theta})}}$ with respect to $\mathbf{X}\boldsymbol{\theta}$. Alike the first approach, this approach is not flawless. For instance, it is not straightforward to recover $E(y|\mathbf{x})$. As a result, the interpretation of θ, i.e. the main goal of modeling, becomes difficult. Moreover, in the log-odds ratio model the transformed dependent variable is not well defined for the boundary values of 0 and 1 of y unless ad-hoc adjustments are made — such as adding an arbitrarily chosen small constant to all observations of y.

The third approach was to use Tobit models. These models are used when there are many observations at the upper and/or lower bound of the fractional response variable. A two-limit Tobit does manage to restrict the predicted values of y between 0 and 1. However, it could be only applied when observations pile up at both extremes. In practice, often observations do not exhibit such characteristic. In addition, Tobit model is appropriate for describing censored data in the interval [0,1] but its application to data defined naturally in that interval is not easy to justify (E. A. Ramalho, Ramalho, & Murteira, 2011). Also, Tobit model holds strict assumption: normality and homoscedasticity of the dependent variable, prior to censoring.

2.2 Maximum and Quasi-Maximum Likelihood

This section first presents a detailed discussion on maximum and quasi-maximum likelihood methods, which lay the foundation for fractional regression models. Following the discussion of the two methods, this section then outlines three types of hypothesis tests that work in a likelihood framework.

2.2.1 Maximum Likelihood

Let $\mathbf{y} = (y_1, y_2, ..., y_n)'$ be an n-dimensional data vector. Suppose the probability density of $\mathbf{y}$ is a member of a family of functions indexed by a finite-dimensional parameter vector $\tilde{\boldsymbol{\theta}} : f(\mathbf{y}; \tilde{\boldsymbol{\theta}})$. The set of all the possible values that $\tilde{\boldsymbol{\theta}}$ could take is called parameter space, which is denoted by $\boldsymbol{\Theta}$. The probability density function $f(\mathbf{y}; \tilde{\boldsymbol{\theta}})$ becomes the true density of $\mathbf{y}$ when the hypothetical parameter vector $\tilde{\boldsymbol{\theta}}$ equals the true parameter vector $\boldsymbol{\theta}$. Moreover, in a model building process, a model is said to be **correctly specified** if the parameter space $\boldsymbol{\Theta}$ includes the true parameter vector. The function $f(\mathbf{y}; \tilde{\boldsymbol{\theta}})$ identifies the data-generating process that underlies an observed sample of data. Also, it yields a mathematical description of the data that the process will produce.

The joint density of n independent and identically distributed (i.i.d.) observations $\mathbf{y} = (y_1, y_2, ..., y_n)'$ is

$$f(\mathbf{y}; \tilde{\boldsymbol{\theta}}) = \prod_{i=1}^{n} f_i(y_i; \tilde{\boldsymbol{\theta}}) = L(\tilde{\boldsymbol{\theta}}|\mathbf{y}).$$

The function $L(\tilde{\boldsymbol{\theta}}|\mathbf{y})$ is the **likelihood function**, which is defined as a function of the unknown parameter $\boldsymbol{\theta}$. Though the joint density and likelihood functions are the same, how they are viewed is different. On one hand, the joint density function is a function of the data conditioned on the parameters. On the other hand, the likelihood function is a function of the parameters, conditioned on the data. To stress on the interest in the parameters, given the the observed data, one can denote the likelihood function as $L(\tilde{\boldsymbol{\theta}}|\textbf{data})$.

In practice, the natural logarithm of the likelihood function is used as it is easier to manipulate algebraically. It is called the log-likelihood function:

$$\log L(\tilde{\boldsymbol{\theta}}|\mathbf{y}) = \sum_{i=1}^{n} \log f(y_i|\tilde{\boldsymbol{\theta}}).$$

The **maximum likelihood (ML)** estimate of the unknown true parameter vector $\boldsymbol{\theta}$ is the $\tilde{\boldsymbol{\theta}}$ that maximizes the likelihood function. Since log transformation is a monotone transformation, maximization of the likelihood function is equivalent to that of the the log likelihood function. Hence, the **maximum likelihood estimator** (**MLE**) of $\boldsymbol{\theta}$ can be defined as

$$\text{MLE of } \boldsymbol{\theta} \equiv \underset{\tilde{\boldsymbol{\theta}} \in \boldsymbol{\Theta}}{\operatorname{argmax}} \log L(\tilde{\boldsymbol{\theta}}|\mathbf{y}).$$

It is apparent that MLE is a maximization problem. Thus, it is crucial to know the conditions under which MLE can be determined using calculus. A **regular** probability density function, say, $f(x;\theta)$, meets the requirement of such conditions. The regularity conditions are given below:

1. The support of the random variable $X, S_X = \{x : f(x;\theta) > 0\}$, does not depend on θ.
2. $f(x;\theta)$ is at least three times differentiable with respect to θ.
3. The true value of θ lies in the compact set of Θ.

Provided that $f(\mathbf{y};\tilde{\boldsymbol{\theta}})$ is regular, MLE can be obtained by differentiating $\log L(\tilde{\boldsymbol{\theta}}|\mathbf{y})$ and solving the first order conditions

$$\frac{\partial \log L(\tilde{\boldsymbol{\theta}}|\mathbf{y})}{\partial \tilde{\boldsymbol{\theta}}} = \mathbf{0}$$

The vector of partial derivatives of the log-likelihood function i.e. the gradient (∇) vector, is called the **score function** or simply **score** and it is denoted by

$$S(\tilde{\boldsymbol{\theta}}|\mathbf{y}) \equiv \frac{\partial \log L(\tilde{\boldsymbol{\theta}}|\mathbf{y})}{\partial \tilde{\boldsymbol{\theta}}}.$$

By definition, the MLE satisfies

$$S(\tilde{\boldsymbol{\theta}}_{mle}|\mathbf{y}) = \mathbf{0}$$

Under random sampling the score for the sample becomes the sum of the scores for each observation y_i:

$$S(\tilde{\boldsymbol{\theta}}|\mathbf{y}) = \sum_{i=1}^{n} \frac{\partial \log f(y_i;\tilde{\boldsymbol{\theta}})}{\partial \tilde{\boldsymbol{\theta}}} = \sum_{i=1}^{n} S(\tilde{\boldsymbol{\theta}}|y_i)$$

where $S(\tilde{\boldsymbol{\theta}}|y_i) = \frac{\partial \log f(y_i;\tilde{\boldsymbol{\theta}})}{\partial \tilde{\boldsymbol{\theta}}}$ is the score associated with y_i.

The matrix of the second moments of the score evaluated at the true parameter vector $\boldsymbol{\theta}$ is called the Hessian:

$$H(\boldsymbol{\theta}|\mathbf{y}) = \frac{\partial^2 \log L(\boldsymbol{\theta}|\mathbf{y})}{\partial \tilde{\boldsymbol{\theta}} \partial \tilde{\boldsymbol{\theta}}'}$$

The **information matrix** is defined as the negative of the Hessian:

$$I(\boldsymbol{\theta}|\mathbf{y}) = -E[H(\boldsymbol{\theta}|\mathbf{y})]$$

If we have random sampling, then

$$H(\boldsymbol{\theta}|\mathbf{y}) = \sum_{i=1}^{n} \frac{\partial^2 \log f(y_i;\tilde{\boldsymbol{\theta}})}{\partial \tilde{\boldsymbol{\theta}} \partial \tilde{\boldsymbol{\theta}}'} = \sum_{i=1}^{n} H(\tilde{\boldsymbol{\theta}}|y_i)$$

and

$$I(\tilde{\boldsymbol{\theta}}|\mathbf{y}) = -\sum_{i=1}^{n} E[H(\tilde{\boldsymbol{\theta}}|y_i)]$$

Considering only the class of unbiased estimators, we define the best estimator as the one with the smallest variance. In the finding process of unbiased estimators, we could use the Cramer-Rao inequality. The theorem claims that the variance of any unbiased estimator is greater than or equal to the inverse of the information matrix.

Cramer-Rao Inequality: Suppose $\mathbf{y}$ is a vector of random variables and its density $f(\mathbf{y};\tilde{\boldsymbol{\theta}})$ satisfies the regularity conditions. Let $L(\tilde{\boldsymbol{\theta}}) \equiv f(\mathbf{y};\tilde{\boldsymbol{\theta}})$ be the likelihood function, and let $\hat{\boldsymbol{\theta}}(\mathbf{y})$ be an unbiased estimator of θ with finite variance-covariance matrix. Then, Crammer-Rao Lower Bound(CRLB) is the inverse of the information matrix:

$$Var[\hat{\boldsymbol{\theta}}(\mathbf{y})] \geq \mathbf{I}(\boldsymbol{\theta})^{-1}.$$

Under weak regularity conditions, assuming the likelihood function is correctly specified, MLE has the following properties:

1. **Consistent** for $\boldsymbol{\theta}$: $\text{plim}(\hat{\boldsymbol{\theta}}) = \boldsymbol{\theta}$;
2. **Asymptotically efficient**;
3. **Asymptotically normally distributed**:

   $$\sqrt{N}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}) = \mathbf{0} \to \mathcal{N}(\mathbf{0}, \boldsymbol{V}),$$

   where $\boldsymbol{V}$ is the asymptotic covariance matrix, and it is, under appropriate regularity conditions, equal to the inverse of the information matrix: $V = \mathbf{I}(\boldsymbol{\theta})^{-1}$.

2.2.2 Quasi-Maximum Likelihood

The quasi-maximum likelihood estimator, $\hat{\boldsymbol{\theta}}_{\text{QML}}$, maximizes a log-likelihood function that is misspecified, which is due to specification of the wrong density. The quasi-MLE is, however, consistent even when the density is partially misspecified, provided that the first moment of the distribution is appropriately specified. For instance, models that are based on densities in the linear exponential family(LEF) e.g. Bernoulli distribution, Normal distribution etc. enjoy this robustness to misspecification.

The quasi-ML estimator may have different asymptotic distribution compared to MLE. In particular, $V = \mathbf{I}(\boldsymbol{\theta})^{-1}$ may no longer be valid. It is, however, possible to derive the asymptotic covariance matrix of the quasi-ML estimator for $\boldsymbol{\theta}$, assuming that $S(\tilde{\boldsymbol{\theta}}|y_i) = \mathbf{0}$. Furthermore, the quasi-maximum likelihood estimator, $\hat{\boldsymbol{\theta}}_{\text{QML}}$, is asymptotically normally distributed:

$$\sqrt{N}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}) \to \mathcal{N}(\mathbf{0}, \boldsymbol{V}),$$

where

$$V = \mathbf{I}(\boldsymbol{\theta})^{-1}\mathbf{J}(\boldsymbol{\theta})\mathbf{I}(\boldsymbol{\theta})^{-1}$$

with $\mathbf{J}(\boldsymbol{\theta}) \equiv \lim_{n\to\infty} \frac{1}{N}\sum_{i=1}^{N} J_i(\boldsymbol{\theta})$

where $J_i(\boldsymbol{\theta}) = E[S_i(\boldsymbol{\theta})S_i(\boldsymbol{\theta})']$.

It is to be noted that quasi-ML estimators are likely to be inefficient due to the issue of misspecification as discussed earlier. Thus, the Likelihood Ratio test, one of the three tests that work in likelihood framework, cannot be used for hypothesis testing when models are based on quasi-maximum likelihood. A further discussion on hypothesis tests is provided in the following section.

2.2.3 Hypothesis Testing in a Likelihood Framework

There are three tests that can be used in likelihood settings, they are the the Wald test, likelihood ratio (LR) test, and the Lagrange multiplier (LM) test (also known as a score test). To discuss them succinctly, suppose that the objective is to test one or more linear restrictions on the K-dimensional parameter vector $\boldsymbol{\theta}$. Restriction(s) can be written as $H_0 : \mathbf{R}\boldsymbol{\theta} = \mathbf{q}$ for some fixed J-dimensional vector $\boldsymbol{q}$, where $\mathbf{R}$ is a $J \times K$

matrix. Furthermore, to avoid redundant restrictions or conflict among restrictions, assume that all rows of $\mathbf{R}$ are linearly independent.

Wald Test

The Wald test uses the result that estimators, under likelihood settings, have asymptotic normal distribution. From this it follows that J-dimensional vector $\mathbf{R}\hat{\boldsymbol{\theta}}$ also has asymptotic normal distribution, given by

$$\sqrt{N}(\mathbf{R}\hat{\boldsymbol{\theta}} - \mathbf{R}\boldsymbol{\theta}) = \mathbf{0} \rightarrow \mathcal{N}(\mathbf{0}, \mathbf{R}\boldsymbol{V}\mathbf{R'}).$$

Under the null hypothesis, $\mathbf{R}\boldsymbol{\theta}$ equals the known vector $\mathbf{q}$ and test statistic could be constructed as

$$\xi_W = N(\mathbf{R}\hat{\boldsymbol{\theta}} - \mathbf{q})'[\mathbf{R}\hat{\boldsymbol{V}}\mathbf{R'}]^{-1}(\mathbf{R}\hat{\boldsymbol{\theta}} - \mathbf{q}),$$

where $\hat{\boldsymbol{V}}$ is a consistent estimator of $\boldsymbol{V}$. Under H_0 this test statistic approximately follows a Chi-squared distribution with J degrees of freedom. That means large values of ξ_W give indication to reject the null hypothesis. Put simply, Wald test investigates whether the difference $\mathbf{R}\hat{\boldsymbol{\theta}} - \mathbf{q}$ is close to zero. If the difference is large and statistically significant, H_0 gets rejected.

Likelihood Ratio Test

To conduct likelihood ratio (LR) test, two models need to be estimated: models with and without restrictions imposed. This means unrestricted estimator $\hat{\boldsymbol{\theta}}$ and restricted estimator $\tilde{\boldsymbol{\theta}}$ are taken into consideration subject to the restriction(s) $\mathbf{R}\boldsymbol{\theta} = \mathbf{q}$. It is likely that maximizing a function without restriction will lead to larger maximum compared to a function with a restriction. Nevertheless, maximum value of a unrestricted function will never be smaller than that of a restricted function. That is, $\log L(\hat{\boldsymbol{\theta}}) - \log L(\tilde{\boldsymbol{\theta}}) \geq 0$. Roughly speaking, if this difference is small, imposed restriction(s) is(are) correct. And, on the other hand, if the difference is large, the restriction(s) is(are) incorrect. More formally, the LR test statistic can be written as

$$\xi_{LR} = 2[\log L(\hat{\boldsymbol{\theta}}) - \log L(\tilde{\boldsymbol{\theta}})],$$

which, under null hypothesis, has an approximate Chi-squared distribution with J degrees of freedom. As usual, large values of ξ_{LR} give indication to reject the null hypothesis.

Lagrange Multiplier Test

The Lagrange multiplier (LM) test is based on the restricted model. It checks whether the first-order conditions from the general model are significantly violated by evaluating the derivative(s) of the concerned function at $\boldsymbol{\theta} = \tilde{\boldsymbol{\theta}}$. Put another way, LM test checks whether $\frac{\partial \log L(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}_{|\tilde{\boldsymbol{\theta}}}}$ is significantly different from zero. The test statistic for the test can be written as

$$\xi_{LM} = \left(\frac{\partial \log L(\tilde{\boldsymbol{\theta}})}{\partial \tilde{\boldsymbol{\theta}}}\right)' [\mathbf{I}(\tilde{\boldsymbol{\theta}})]^{-1} \left(\frac{\partial \log L(\tilde{\boldsymbol{\theta}})}{\partial \tilde{\boldsymbol{\theta}}}\right),$$

Under H_0, LM has limiting chi-squared distribution with J degrees of freedom. Again, large values of ξ_{LM} give indication to reject the null hypothesis. Since LM test is based based on the score vector, this test is also known as the score test.

2.3 Fractional Regression Models

There are mainly two approaches for modeling fractional response variables without boundary observations. The first approach uses nonlinear models that requires only the correct specification of the conditional expectation of the fractional response variable. The second approach uses the same nonlinear models and in addition assumes a particular conditional distribution, beta distribution to be specific, for the fractional response variable. E. A. Ramalho et al. (2011) point that only the first approach is applicable when there are a finite number of boundary observations. The following subsections present discussion on the two approaches mentioned above.

2.3.1 QML Estimators

To deal with fractional response variables, Papke and Wooldridge (1996) were the first to propose that only the assumption on functional form for y is required. That is, the functional form should impose desired constraints on the conditional mean of the dependent variable:

$$E(y|\mathbf{x}) = G(\mathbf{X}\boldsymbol{\theta}),$$

where $G(.)$ is a known nonlinear function satisfying $0 \leq G(.) \leq 1$. They suggested that any cumulative function, in this process, works as a possible specification for $G(.)$. In this case, logistic function is an obvious choice. However, instead of using linearization first as discussed earlier, estimation should be done directly using nonlinear techniques.

E. A. Ramalho et al. (2011) point that a model, which is defined by the equation $E(y|\mathbf{x}) = G(\mathbf{X}\boldsymbol{\theta})$, can be estimated in two ways. First, using nonlinear least squares which was used in an empirical application by Hermalin and Wallace (1994). Second, using QML as suggested by Papke and Wooldridge (1996). In the latter case, the authors used a particular QML method based on Bernoulli log-likelihood function. It can be expressed as follows

$$LL_i(\theta) = y_i \log[G(x_i\theta] + (1 - y_i)\log[1 - G(x_i\theta)].$$

As discussed in section 2.2.2, Bernoulli distribution is a member of the linear exponential family(LEF), hence the QML estimator of θ defined by

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \sum_{i=1}^{N} LL_i(\theta)$$

is consistent and asymptotically normal, regardless of the true distribution of y conditional on x, provided that $E(y|\mathbf{x})$ discussed above is correctly specified. The asymptotic distribution of the QML estimator, as discussed earlier, is given by

$$\sqrt{N}(\boldsymbol{\hat{\theta} - \theta}) \rightarrow \mathcal{N}(\mathbf{0}, \boldsymbol{V}).$$

2.3.2 The Beta Fractional Regression Model

A beta regression model could be employed when the value of the dependent variable is greater than zero but less than one i.e. $0 < y < 1$. It uses a parameterization of the beta distribution in terms of its mean and dispersion (or precision) parameters. This is because the standard beta density function is based on shape parameters and in practice they are of little interest. Thus, for modeling purposes, a simplified parameterization of the beta density is used. E. A. Ramalho et al. (2011) note that Paolino (2001) and Ferrari and Cribari-Neto (2004) independently proposed the mean-dispersion parametrization of the beta density. The modified parameterization makes the interpretation of beta regression models significantly simpler. These simpler beta regression models are, in fact, similar to QML models discussed previously.

The standard beta density function could be expressed in the following way

$$f(y; p, q) = \frac{\Gamma(p+q)}{\Gamma(p)\Gamma(q)} y^{(p-1)}(1-y)^{(q-1)},$$

where $\Gamma(.)$ denotes the gamma function, $p > 0$ and $q > 0$ are shape parameters. By contrast, letting $p = \mu\phi$ and $q = (1-\mu)\phi$, a mean-dispersion parameterization of the beta density could be expressed as

$$f(y; \mu, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma[(1-\mu)\phi]} y^{(\mu\phi-1)}(1-y)^{(1-\mu)\phi-1},$$

where $0 < \mu < 1$ and $\phi > 0$. This implies that

$$E(y) = \frac{p}{p+q} = \mu$$

and

$$Var(y) = \frac{pq}{(p+q)^2(p+q+1)} = \frac{\mu(1-\mu)}{\phi+1}.$$

Here ϕ can be regarded as precision parameter with the notion that, for a constant μ, as the value of ϕ gets larger the smaller the variance of y becomes.

E. A. Ramalho et al. (2011) mention about two beta regression models that could be applied based on the simplified beta density function. The first model simply assumes $\mu = G(\mathbf{X}\boldsymbol{\theta})$ as in the models discussed in the previous section and consider ϕ as a nuisance parameter. In the second model, the precision parameter and the mean are estimated differently. The model assumes that $\mu = G(\mathbf{X}\boldsymbol{\theta})$ and $\phi = \exp(\mathbf{z}\boldsymbol{\alpha})$, where $\mathbf{z}$ is a set of independent variables, potentially distinct from $\mathbf{x}$, and $\boldsymbol{\alpha}$ is a vector of parameters. The interest of this model is in analyzing whether a variable contributes to the variance of y beyond its effect upon the mean. In addition, both models are estimated by maximizing the log-likelihood function of the simplified beta density function. Hence, as in the case of MLE, estimators of these regression models are consistent and efficient. Rather than duplicating the result, it should be noted that the resulting estimators have the exact asymptotic distribution of MLE as discussed in section 2.2.1.

Chapter 3

Application: Analysing Determinants of Capital Structure

This chapter presents an application of fractional regression models, where the aim is to analyse capital structure of European manufacturing firms. The first section presents two standard theories on capital structure, and the second section, based around these two theories, presents five general hypotheses. In the third section, the main hypotheses of the application are formulated. Then the subsequent sections analyse the data and apply fractional regression models.

3.1 Capital Structure Theories

There is no single theory that can fully explain firms' decisions on capital structure. Rather there are a few, each more or less helpful, conflicting theories on debt versus equity choices. These theories try to explain a particular firm's decision on capital structure based on its assets, operations, and circumstances. Among these theories the most well-known are the trade-off theory and the pecking order theory.

Trade-off Theory

Trade-off theory (TOT), which was initially introduced by Kraus and Litzenberger (1973), claims the existence of optimal capital structure and it is determined by the trade-off between the benefits of debt and cost of debt. According to this theory, companies with safe, tangible assets, and significant taxable income that enjoy the benefit of tax shield are likely to have high target debt ratios. By contrast, companies with risky and intangible assets rely mainly on equity financing. Put simply, if there were no cost associated with debt, tax advantage would provide firms enough incentive to opt for full debt financing. In real world, however, debt cannot be issued at free of cost.

The primary concern when issuing debt is the increase in expected bankruptcy costs. This expected bankruptcy costs can be thought as a product of the probability of bankruptcy and the direct and indirect cost of bankruptcy (Damodaran, 2014). Major direct costs of bankruptcy include legal and administrative costs, restructuring costs, and credit costs. A bankrupt firm is perceived to be in trouble. Hence, as an indirect cost, customers may stop buying the firm's products or services. Moreover, the firm may face declining vendor relationship and experience difficulty in raising fresh capital.

Agency costs represent another drawback of issuing debts. Jensen and Meckling (1976) maintain that managers tend to focus more on maximization of equity value rather than total firm value. When inundated with cash flow as a result of issuance of debt, managers favor risky projects with the hope that successful project would benefit shareholders. Rational debtholders, however, are aware of this fact and demand a risk premium which, in turn, increases the interest rate. As a result, firms do not get much incentive to issue debts.

Pecking-order Theory

The pecking-order theory (POT), which was originally developed by Myers (1984) and Myers and Majluf (1984), takes asymmetric information into account and claims that firms do not have the luxury to have optimal capital structure. This theory tells that managers have more information than outside investors as far as companies' prospects, risks, and values are concerned. As a consequence, this asymmetric information affects the decisions on capital structure. According to this theory, firms tend to adopt a sequence of financial decisions. Initially, investment is funded with internal funds (retained earnings). Then, if external financing is needed, firms issue safest debt first. Finally, only when firms run out of debt capacity, they issue new shares as a last resort.

Optimal debt-equity mix, according to pecking-order theory, is not achievable due to the existence two types of equity. In fact, in pecking order of financing, internal equity comes first whereas external equity comes at last. This theory explains that most profitable firms borrow less because they do not need external funds. Moreover, less profitable firms with insufficient funds borrow more because debt financing comes first in the pecking order of external financing.

3.2 General Empirical Hypotheses

Based on some empirical studies done previously by various researches and also using theories of capital structure discussed above, the section presents five hypotheses for firms'' financing decisions.

1. *Size is positively related to debt*: Capital structure varies depending on the size of the firm. Larger firms are likely to have higher debt ratios. Warner (1977), in fact, argues that larger firms are more likely to be diversified and it is unlikely that they would face bankruptcy. Moreover, larger firms have more access to non-bank debt financing as they are likely to have credit rating. Myers (1984) also argues that it easier for larger firms to obtain debt as informational asymmetries are less severe for them. In short, both TOT and POT agree that size is positively related to debt.

2.*Tangibility is positively related to debt*: Firms with greater tangible assets i.e. high ratios of fixed assets to total assets have higher debt ratios. Myers (1977) supports this fact by arguing that tangible assets, in the case of liquidation, maintain their value so debt holders have less to worry about when firms have significant tangible assets. Also, due to asymmetric information, lenders rely heavily on tangible assets. So, firms with larger proportion of tangible assets are likely to have access to debt market. In this case, both TOT and POT agree that tangibility is positively related to debt.

3. *Liquidity is negatively related to debt*: Myers and Majluf (1984) maintain that firms that prefer internal financing tend to create liquid reserves from retained earnings. This liquidity reserves, in turn, helps the firms to finance future investments. That is, firms require less external financing. Clearly, this point is supported by POT.

4. *Profitability is maybe positively or negatively related to debt*: In the negative case, debt ratios are lower for profitable firms. Myers (1984) argument could be used in support of this point. That is, profitable firms have greater availability of internal capital so there is less need for external funds. Jensen and Meckling (1976), however, disagree. According to them, firms with higher profitability have tax advantage of using debt and it is unlikely that such firms would be unable to pay the interests. In other words, firms with higher profitability have incentives to obtain debt and also have to the ability to attract debt-holders. In short, POT approves the fact that profitability is negatively related to debt whereas TOT claims the opposite.

5. *Expected growth maybe positively or negatively related to debt*: Some researchers maintain that firms with expected growth are possibly reluctant towards obtaining debt. For instance, Frank and Goyal (2009) find that growth opportunities lead to an increase in the cost of financial distress which, in turn, may offset

the tax benefits of debts. So, firms with growth opportunities don't have incentive to obtain debt. Clearly, this negative relation between debt and expected growth is supported by TOT. Shyam-Sunder and Myers (1999), however, disagree and find that firms with expected growth opportunities borrow more. They argue that firms opt for external financing because when expected growth is higher it is likely that firms will outrun internally generated funds. This positive relation is, of course, supported by POT.

3.3 Main Hypotheses

Besides investigating the effects of usual determinants of capital structure, this paper has three main goals. First, to study the difference between High-Tech and Low-Tech firms in terms of their capital structure. Second, to examine whether the choice of debt-equity varied before and after the global financial crisis. Third, to analyse capital structures of SMEs and large firms before and after the crisis. Based on these goals, the following hypotheses are formulated.

1. *High-Tech firms have lower leverage ratio than Low-Tech firms*: Notwithstanding the insignificant number of empirical studies done on the capital structure of High-Tech firms, it is expected that leverage ratio will be lower for High-Tech firms. In other words, these firms tend to rely heavily on internal funds. For instance, U.S. tech giant Apple Inc., which was founded in 1976, remained as a zero-leverage firm for many years. In fact, the company issued bonds for the first time in 1994. It returned to the debt market for the second time after a hiatus in 2013. Furthermore, Aghion, Bond, Klemm, and Marinescu (2004) claim that innovative firms are likely to be less reliant on debt finance to minimize the expected bankruptcy costs. According to these authors, innovative firms have higher risk of bankruptcy for a given level of debt because these firms have higher proportion of intangible assets such as knowledge and reputation, and use more specialized equipment.

2. *Financial crisis may affect leverage*

(a) Positively: Frank and Goyal (2009) refer to Gertler and Gilchrist (1993), and maintain that subsequent to recessions, which is due to monetary contractions, aggregate net debt issues increase for large firms but remain stable for small firms. So, debt-to-equity ratios of firms, in general, do not fall due to crisis. Rather, crisis affects leverage positively.

(b) Negatively: Financial crisis engenders a great deal economic uncertainty, and investment opportunities, in turn, become rare. Consequently, the need for external capital becomes weak, and it leads to reduction in firms' leverage ratios (Graham, Leary, & Roberts, 2014). So, on the basis of this fact, crisis affects leverage negatively.

3. *SMEs, compared to large firms, take less debt in the after-crisis period*: Fosberg (2012) argues that when financial crisis occurs interbank lending rates increase due to lack of banks' confidence on each other's financial securities. As a result, supply of loans to non-financial firms decreases. This reduced supply of loan implies that SMEs get less access to bank loans than large firms as the latter type of firms, in general, are considered to be more creditworthy than the former. Put another way, SMEs need to alter their financial mix i.e. rely less on debts subsequent to financial crisis.

3.4 The Data

The data used in this study were obtained from Amadeus (Bureau van Dijk), a database of comparable financial and business information on European companies. From the Amadeus database, information about balance sheets, income statements and other characteristics of manufacturing firms for the year 2007 and 2013 were drawn, and countries namely, Portugal, Greece, France, and Germany were considered. To be specific, manufacturing firms that fall into either High-Tech or Low-Tech category were taken into consideration using Eurostat definition. For details see Table 3.1. Moreover, the study deals only with companies

Table 3.1: Eurostat Definition of High-Tech and Low-Tech

Manufacturing industries	**NACE Rev. 2 codes – 3-digit level**
High-technology	21 Manufacture of basic pharmaceutical products and pharmaceutical preparations 26 Manufacture of computer, electronic and optical products 30.3 Manufacture of air and spacecraft and related machinery
Low-technology	10 to 17 Manufacture of food products, beverages, tobacco products, textiles, wearing apparel,leather and related products, wood and of products of wood, paper and paper products 18 Printing and reproduction of recorded media excluding 18.2 Reproduction of recorded media 31 Manufacture of furniture 32 Other manufacturing excluding 32.5 Manufacture of medical and dental instruments and supplies

that are active and have unconsolidated accounts, and excludes firms that have negative equity.

This study uses pooled cross sections, and to capture the effect of the financial crisis, as an obvious case, uses a dummy variable. The variable CRISIS equals 1 if data correspond to year 2013 and 0 otherwise. That is, the base year is 2007. Furthermore, this study incorporates another dummy variable, SME, to find whether capital structure varies according to firms' size. Here, SME equals 1 if firms are small or medium sized, and equals 0 for large firms. The study uses the definitions provided by European Commission (recommendation 2003/361/EC) to categorize firms based on their sizes. By definition, SMEs are those 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. HIGHTECH is another dummy variable that equals 1 for High-Tech firms, and 0 for Low-Tech firms. Finally, the last dummy variable that is used in this study is SMECRISIS, which is basically an interaction term generated by interacting SME and CRISIS.

Similar to J. J. S. Ramalho and Silva (2009), this paper measures leverage as the ratio of long-term debt (LTD) to long-term capital assets. Here, the denominator is defined as the sum of LTD and equity. And, equity is simply shareholders' funds. To obtain realistic values of leverage, in the data cleaning process LTD < 0, which is due to measurement error, was dropped as such value is not feasible from accounting perspective. Also, capital assets ≤ 0 was dropped. This study ignores observations with missing values. Most of the determinants that appear in the hypotheses discussed previously correspond to observable theoretical attributes. So, to conduct econometric analysis, this paper uses explanatory variables that work as proxies for those attributes. Table 3.2 presents the attributes and their proxies, which are widely used in empirical research. Theoretically, the values of the variables TANGIBILITY and LIQUIDITY are expected to stay between 0 and 1. So, any observation that did not meet this criteria were dropped during the data cleaning process.

Table 3.3-6 report some descriptive statistics for the explanatory variables for each country.[1] In all cases, mean LEVERAGE is quite low [2]. Portugal has the highest mean, which is 0.366. Greece, France, and Germany have mean LEVERAGE 0.152, 0.233, and 0.351 respectively. The variable GROWTH shows greater variations across countries with high standard deviations. Mean GROWTH for Portugal, Greece, France, and Germany are respectively 9.098, 7.177, 4.242, and 2.184. Mean SIZE for Portugal and France are quite similar,6.233 and 6.553 respectively. Besides, for Greece and Germany mean SIZE are respectively 7.556 and 8.947. The mean PROFITABILITY for Portugal and Greece are very close, being 0.040 and 0.046. And for France and Germany they are 0.066 and 0.127 respectively. Noticeably, Germany has the highest mean PROFITABILITY. Mean TANGIBILITY is roughly the same for Portugal, Greece, and Germany, being 0.486, 0.500, and 0.513 respectively. Besides, France has the lowest mean TANGIBILITY, which is 0.332. The last continuous explanatory variable is LIQUIDITY. The mean of this variable for Portugal, Greece, France, and Germany are 0.186, 0.159, 0.332, and 0.146 respectively. The categorical variables, whose descriptive statistics are worth analyzing, are HIGHTECH and SME. The mean HIGHTECH happens to be

[1] The monetary variables are measured in thousands of euros.

[2] For Portugal, Greece, France and Germany the number of zero-debt firms are respectively $1,666$, $1,920$, $12,468$, and 766.

Table 3.2: Independent Variables

	Proxy	
Attributes	**Name**	**Definition**
Tangibility	TANGIBILITY	Sum of tangible assets and inventories, divided by total assets
Size	SIZE	Natural logarithm of sales
Profitability	PROFITABILITY	Ratio between earnings before interest and taxes (EBIT) and total assets
Expected growth	GROWTH	Percentage change in total assets
Liquidity	LIQUIDITY	Sum of cash and marketable securities, divided by current assets

low in all cases, which in turn implies that there are fewer number of High-Tech firms in the samples. In fact, Germany has the highest mean HIGHTECH, which is 0.263. For Portugal, Greece, and France, the means of the variable are respectively, 0.018, 0.049, and 0.061. The mean SME appears to be high for two countries. To be specific, Portugal and Greece have mean SME 0.971 and 0.873 respectively, which means that SMEs are dominant in numbers in the samples for these countries. Besides, mean SME for France and Germany are quite close, being 0.399 and 0.410 respectively. This implies that large firms dominate in the samples for these two countries. The means of other two dummy variables, CRISIS and SMECRISIS, are trivial and basically corresponds to the percentage of firms for each year. For instance, in the case of Portugal, mean CRISIS is 0.639. This means that there are more observations for the year 2013 than that of 2007.[3]

Figures 3.1-4 present four different kernal density plots of leverage, which are categorized by country, use of technology, type of firms, and crisis-period. All the four plots exhibit a common pattern: plots are right skewed. This particular pattern indicates that most firms, regardless of their categorization, have leverage below 50%. Figure 3.1 reveals that LEVERAGE distribution of the Greek firms is the most peaked. That is, firms in Greece take less debt compared to other other countries. Figure 3.2 shows that leverage, in general, vary by High-Tech and Low-Tech firms. In fact, leverage distribution of High-Tech firms is more peaked than that of Low-Tech firms. Put another way, High-Tech firms comparatively take less debt. Figure 3.3 gives an indication that leverage of SMEs and large firms do not differ significantly. Although, leverage distribution of large firms is slighly more peaked than that of SMEs, indicating large are likely to take less debt than SMEs. Last, Figure 3.4 shows that leverage of firms in general, loosely speaking, did not vary by much before and after the crisis because the density plots look almost identical.

Table 3.3: Summary Statistics-Portugal

Variable	Mean	Std. Dev.	Min.	Max.
LEVERAGE	0.366	0.283	0	1
CRISIS	0.639	0.480	0	1
HIGHTECH	0.018	0.132	0	1
SME	0.971	0.168	0	1
SMECRISIS	0.621	0.485	0	1
GROWTH	9.098	27.781	-77.029	199.629
SIZE	6.233	1.730	-2.083	14.194
PROFITABILITY	0.040	0.110	-1.816	0.997
TANGIBILITY	0.486	0.249	0	0.998
LIQUIDITY	0.186	0.220	0	1
N		13457		

[3]In the sample, Portugal, Greece, France, and Germany have 8,596, 2,054, 29,351, and 2,810 firms respectively when CRISIS=1 i.e. in 2013. And when CRISIS=0 i.e. in 2007, the numbers are respectively 4,861, 1,746, 12,868, and 259.

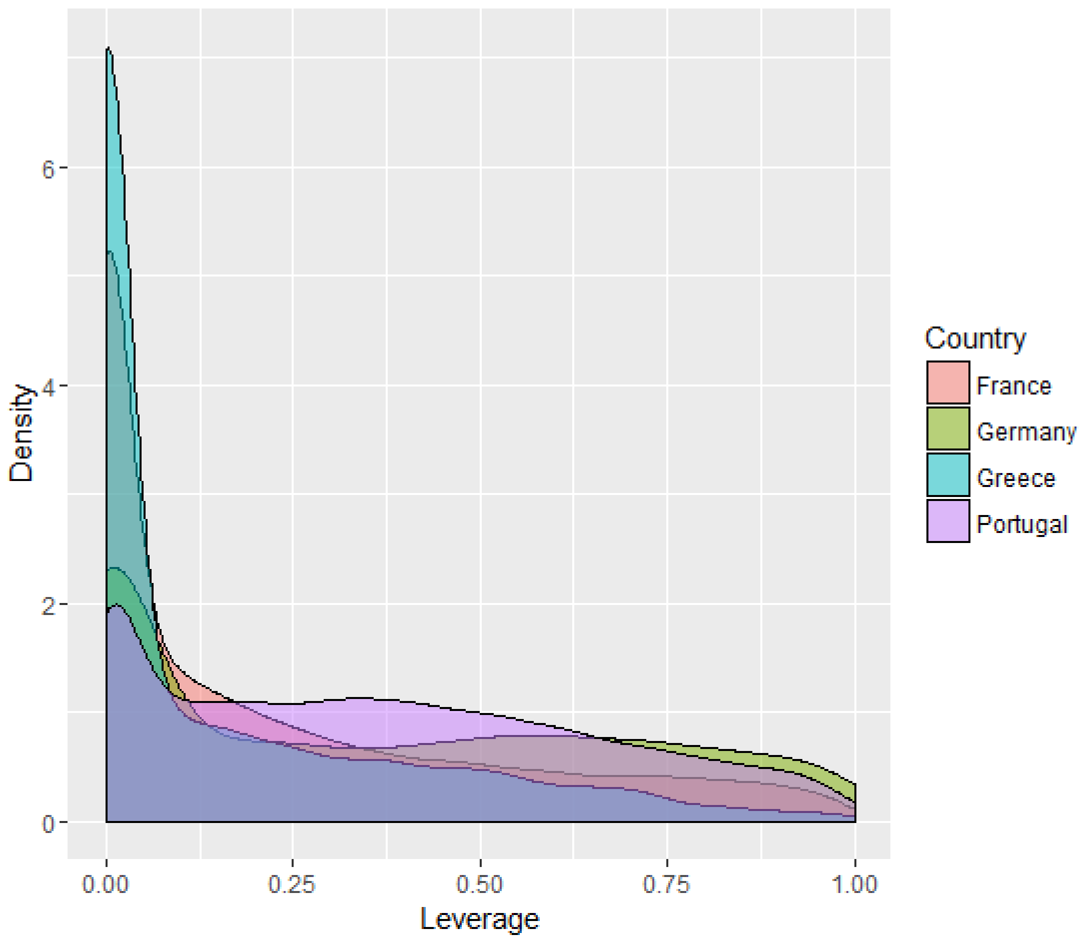

Figure 3.1: Distribution of Leverage by Country

Table 3.4: Summary Statistics-Greece

Variable	Mean	Std. Dev.	Min.	Max.
LEVERAGE	0.152	0.230	0	0.999
CRISIS	0.541	0.498	0	1
HIGHTECH	0.049	0.217	0	1
SME	0.873	0.333	0	1
SMECRISIS	0.493	0.500	0	1
GROWTH	7.177	24.215	-65.505	196.603
SIZE	7.556	1.584	-2.263	12.984
PROFITABILITY	0.046	0.090	-0.743	0.683
TANGIBILITY	0.500	0.222	0	0.995
LIQUIDITY	0.159	0.178	0	0.977
N		3800		

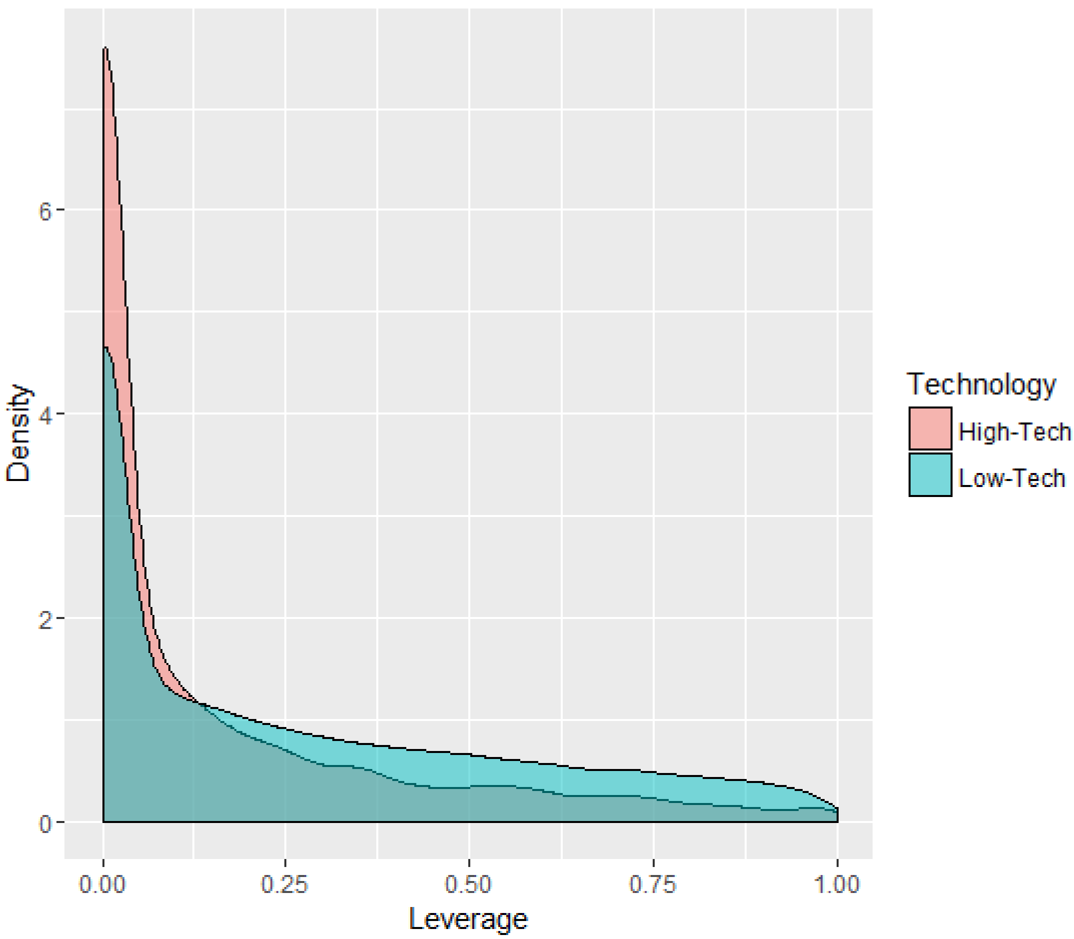

Figure 3.2: Distribution of Leverage by Technology

Table 3.5: Summary Statistics-France

Variable	Mean	Std. Dev.	Min.	Max.
LEVERAGE	0.233	0.279	0	1
CRISIS	0.695	0.460	0	1
HIGHTECH	0.061	0.240	0	1
SME	0.399	0.490	0	1
SMECRISIS	0.247	0.431	0	1
GROWTH	4.242	44.389	-99.998	199.824
SIZE	6.553	1.728	-5.521	16.274
PROFITABILITY	0.066	0.143	-3.020	2.283
TANGIBILITY	0.332	0.221	0	0.998
LIQUIDITY	0.332	0.271	0	1
N		42219		

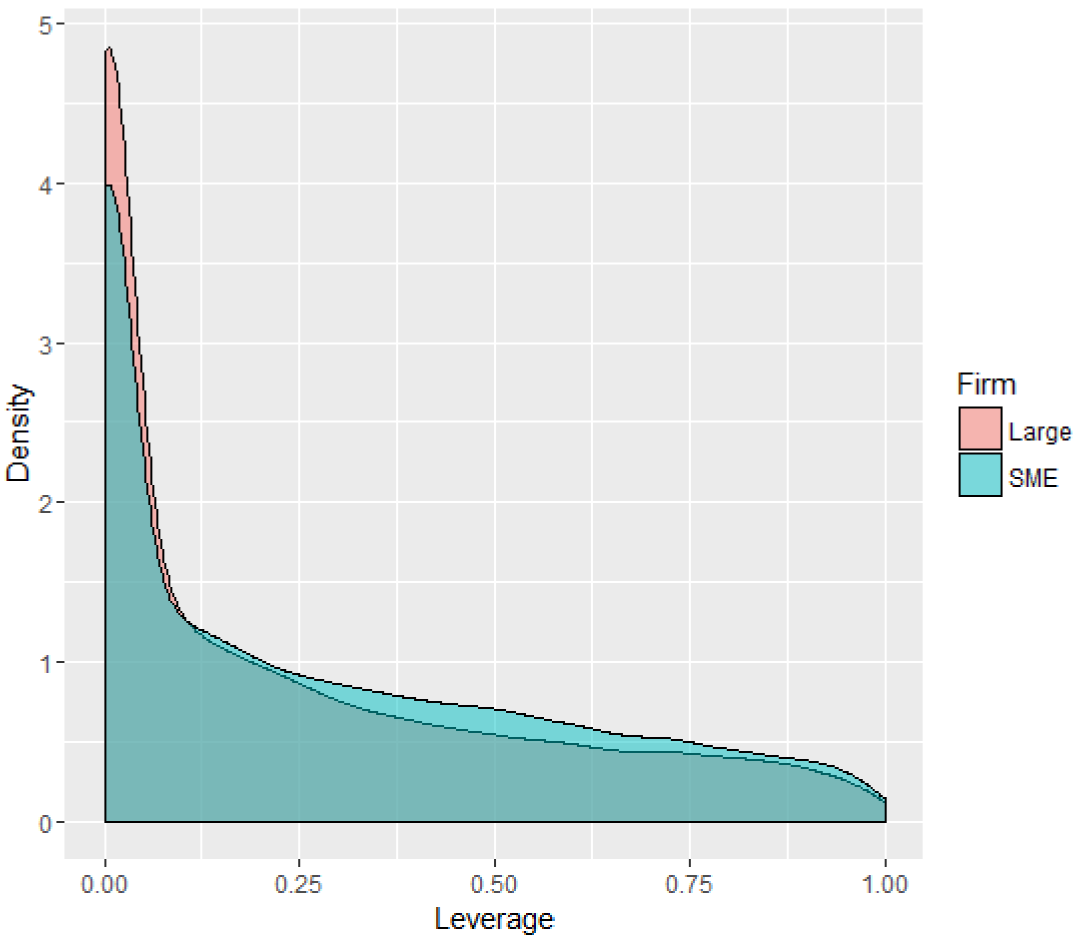

Figure 3.3: Distribution of Leverage by type of Firm

Table 3.6: Summary Statistics-Germany

Variable	Mean	Std. Dev.	Min.	Max.
LEVERAGE	0.351	0.328	0	1
CRISIS	0.916	0.278	0	1
HIGHTECH	0.263	0.440	0	1
SME	0.410	0.492	0	1
SMECRISIS	0.370	0.483	0	1
GROWTH	2.184	25.956	-96.449	188.417
SIZE	8.947	2.039	-0.079	15.632
PROFITABILITY	0.127	0.259	-1.525	7.366
TANGIBILITY	0.513	0.242	0	0.997
LIQUIDITY	0.146	0.187	0	0.977
N		3069		

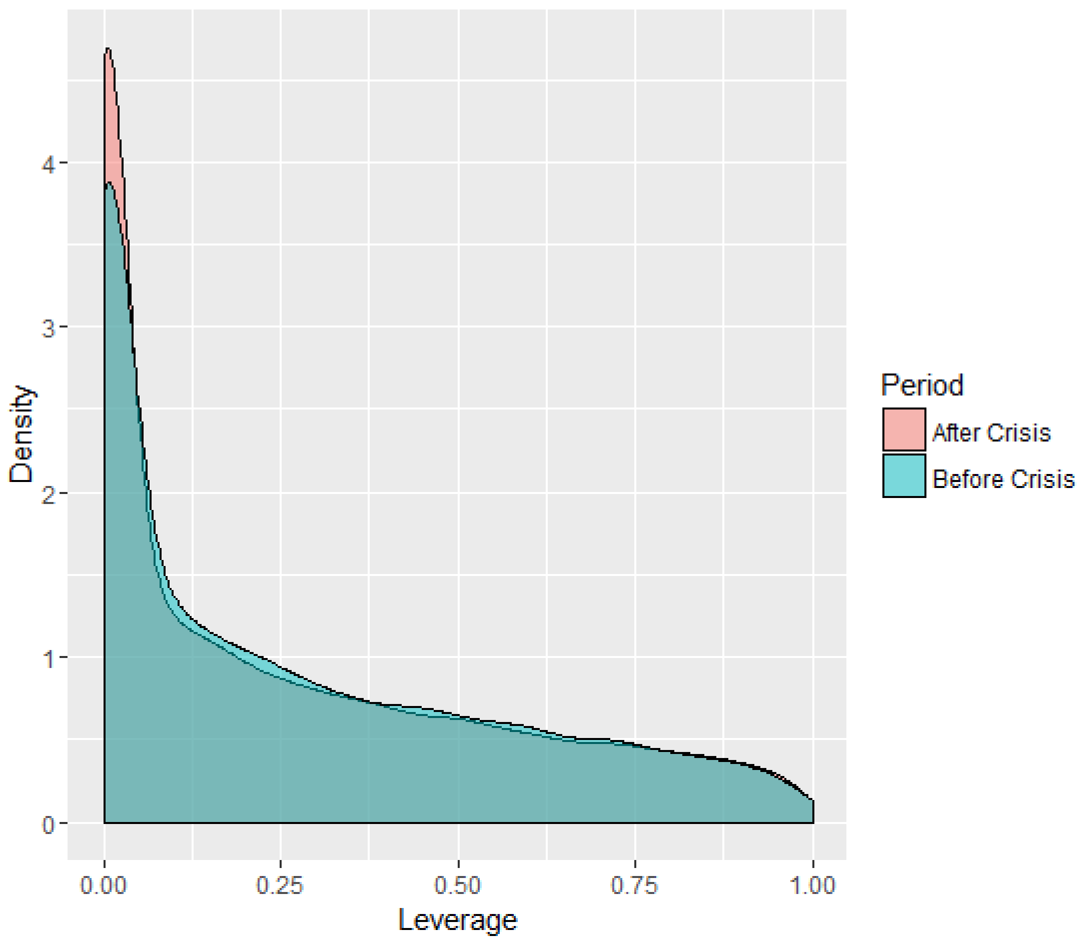

Figure 3.4: Distribution of Leverage by Period

3.5 Empirical Results

3.5.1 Main Findings

To estimate the QML model, this study primarily considers the logit specification discussed in Chapter 2. That is,

$$E(\text{LEVERAGE}|\mathbf{x}) = G(\beta_0+\beta_1\text{CRISIS}+\beta_2\text{HIGHTECH}+\beta_3\text{SME}+\beta_4\text{SMECRISIS}+\beta_5\text{GROWTH}+\beta_6\text{SIZE} + \beta_7\text{PROFITABILITY} + \beta_8\text{TANGIBILITY} + \beta_9\text{LIQUIDITY}), \quad (3.1)$$

where $G(.)$ is the logistic function. Table 3.7 presents the empirical results for Portugal, Greece, France and Germany obtained from estimating the equation (3.1).

Table 3.7: Estimation Results: Main Model (QML Logit)

VARIABLES	(1) Portugal	(2) Greece	(3) France	(4) Germany
CRISIS	-0.530***	0.070	0.158***	-0.895***
	(0.139)	(0.184)	(0.023)	(0.113)
HIGHTECH	-0.100	-0.565***	-0.759***	-0.400***
	(0.081)	(0.156)	(0.038)	(0.062)
SME	0.160	0.126	0.166***	0.593***
	(0.097)	(0.111)	(0.027)	(0.122)
SMECRISIS	0.143	0.046	-0.063*	-0.927***
	(0.140)	(0.194)	(0.033)	(0.133)
GROWTH	0.005***	0.004***	0.001***	0.004***
	(0.000)	(0.001)	(0.000)	(0.001)
SIZE	-0.092***	0.216***	-0.151***	-0.170***
	(0.007)	(0.021)	(0.005)	(0.015)
PROFITABILITY	-1.191***	-1.919***	-0.281***	-0.077
	(0.133)	(0.368)	(0.056)	(0.104)
TANGIBILITY	0.971***	1.023***	1.492***	1.714***
	(0.048)	(0.156)	(0.037)	(0.122)
LIQUIDITY	-0.822***	-1.256***	0.163***	-1.605***
	(0.057)	(0.231)	(0.033)	(0.163)
Constant	-0.223*	-3.851***	-0.904***	1.203***
	(0.117)	(0.229)	(0.044)	(0.145)
Observations	13,457	3,800	42,219	3,069

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

One of the main interests of this study, mentioned earlier, is to find out how High-Tech firms raise their capital. The coefficient of the variable HIGHTECH is statistically significant across all countries except for Portugal. And, without any surprise, the sign of the coefficient of HIGHTECH in all four cases is negative. This negative sign indicates that High-Tech firms on average prefer to raise funds internally. In fact, based on discussion provided in section 3.3, this sign was expected.

Another major interest of this study is to see the impact of financial crisis on the capital structures of firms. The variable of interest is CRISIS and it is statistically significant for all countries except Greece. The sign of the coefficient of this year dummy variable varies across countries. This means firms, on the basis of their leverage ratios, did not act in similar fashion subsequent to crisis. In fact, firms in Germany and Portugal on average took less debt in year 2013 compared to 2007. On the other hand, France acted differently. The sign for the coefficient of CRISIS is positive. That is, firms borrowed more in 2013 compared to 2007. In this case, the study of Gertler and Gilchrist (1993) is supporting the positive sign.

To find out how SMEs, compared to large firms, financed their capital before and after the crisis, it is inevitable to apply difference-in-differences(DID) method. Based on the main model i.e. using equation 3.1, Table 3.8 presents the general DID setup. Furthermore, Table 3.9-3.10 present the corresponding calculations for France and Germany for whom the variable SME and SMECRISIS are statistically significant. DID formulation suggests that $\beta_1 + \beta_4$, second row last column, should be used to find out whether SMEs took more or less debt in 2013 than in 2007. And, β_4, last row last column, should be used to find out whether SMEs took more or less debt than large firms in 2013 than in 2007. Results reveal that in France SMEs took more debt in 2013. By contrast, in Germany SMEs took less debt in 2013. Furthermore, results confirm that SMEs in both of the countries on average took less debt than large firms in the after-crisis period. The latter finding, in fact, corroborates the hypothesis formulated previously that SMEs, compared to large firms, on average take less debt during crisis.

Table 3.8: Difference-in-Differences Estimator

	Before	**After**	**After-Before**
Large	β_0	$\beta_0 + \beta_1$	β_1
SME	$\beta_0 + \beta_3$	$\beta_0 + \beta_3 + \beta_1 + \beta_4$	$\beta_1 + \beta_4$
SME-Large	β_3	$\beta_3 + \beta_4$	β_4

Table 3.9: Difference-in-Differences Estimator-France

	Before	**After**	**After-Before**
Large	-0.904	-0.746	$+0.158$
SME	-0.738	-0.643	$+0.095$
SME-Large	$+0.166$	$+0.103$	-0.063

Table 3.10: Difference-in-Differences Estimator-Germany

	Before	**After**	**After-Before**
Large	$+1.203$	$+0.308$	-0.895
SME	$+1.796$	-0.026	-1.822
SME-Large	$+0.593$	-0.334	-0.927

TANGIBILITY and GROWTH are statistically significant for all countries. Moreover, in all cases, their coefficients have positive sign. That is, the variables are positively related with debt. In the case of TANGIBILITY, the positive sign of its coefficient is not surprising at all because both pecking-order and trade-off theory predict this positive relationship. In short, the coefficient of TANGIBILITY has the expected sign. In the case of GROWTH, the pecking-order theory is predicting correctly allowing for the fact that increased expected growth depletes internally generated funds. Another variable that is statistically significant across all the countries is SIZE. In all cases except for Greece, the coefficient of the variable maintains a negative sign. Interestingly, pecking-order theory and trade-off theory suggest a positive sign. That is, only in the case of Greece, theories are predicting correctly. The negative relationship between SIZE and debt that is apparent in the case of Germany, France, and Portugal can be backed by the findings of Strebulaev and Yang (2013). The authors claim that a significant number of large public nonfinancial US firms maintain a zero-debt or almost zero-debt policy. So, it might be the case that same phenomenon exists for European manufacturing firms. The variable LIQUIDITY is also statistically significant in all four cases. Except for France, there appears to be a negative relationship between LIQUIDITY and debt. So, both pecking-order theory and trade-off theory are predicting correctly in the case of Germany, Greece, and Portugal. By contrast, firms in France despite their high liquidity opt for debt probably to gain tax benefits. Last, the variable PROFITABILITY, which is statistically significant for France, Greece, and Portugal, exhibits negative relationship with debt. Here, the pecking-order theory, which argues that profitable firms tend to have more internal funds, is predicting correctly.

3.5.2 Robustness Tests

This sub-section has three aims. One, to examine whether estimates of a model change significantly when specification for G(·) changes. Two, to find out if the large number of zero-debt firms affect the regression results. Three, to find out whether alternative estimation methods i.e ML and QML produce significantly different results. In doing so, this sub-section first makes the use of two additional models: QML probit and QML cloglog, and compares their results with that of the main model. See Table 3.11 for details of the models' specifications. Then, it employs QML logit model to a new sample which excludes zero-debt firms, and compares the estimates with that of the main model. Last, this sub-section employs QML logit and Beta logit models to the new sample, and compares the results. Tables 3.12-15 present the estimates of the new models for each country. These tables, for the ease of comparison, also include the result of the main model. To avoid confusion, in the discussion of the regression results which follows next, the QML logit for the full sample is referred to as the main model, and the QML logit for the restricted sample is simply referred to as QML logit(4).

Table 3.11: Specifications

Model Designation	Distribution Function	Cumulative Distribution $G(\mathbf{X}\boldsymbol{\theta})$
Logit	Logistic	$\frac{e^{(\mathbf{X}\boldsymbol{\theta})}}{1+e^{(\mathbf{X}\boldsymbol{\theta})}}$
Probit	Standard normal	$\boldsymbol{\Phi}(\mathbf{X}\boldsymbol{\theta})$
Cloglog	Extreme minimum	$1-\frac{e^{(\mathbf{X}\boldsymbol{\theta})}}{1+e^{(\mathbf{X}\boldsymbol{\theta})}}$

The estimates of the additional QML models are very similar to that of the main model. In fact, except for the variable SME in the case of Portugal, all the variables which are significant in the main model remain significant with same significance levels and signs across all QML models. In the QML probit model for Portugal, the variable SME is statistically significant only at 10% significance level with a positive coefficient. By contrast, in the main model and QML cloglog model the variable is statistically insignificant. Overall, the estimates of QML probit, QML cloglog, and the main model do not contradict.

The estimates of the main model and QML logit model differ in terms of variables' significance levels in a few cases. In the main model for Portugal, the variable CRISIS is statistically significant at 1% significance level. Whereas, in the QML logit(4) model the variable is statistically significant only at 10% significance level. In both cases, however, the sign of the coefficient remains the same. In the main model for Greece, the variables HIGHTECH and SIZE are statistically significant at 1% significance levels. However, in the QML logit(4) model these variables become statistically insignificant. In the main model for France, the variable SMECRISIS is statistically significant only at 10% significance level. By contrast, the variable becomes statistically insignificant in the QML logit(4) model. Last, in the main model for Germany the variable GROWTH is statistically significant at 1% significance level. Whereas, in the QML logit(4) model the variable becomes statistically insignificant. Some of the above cases, where highly significant variables become insignificant, hint that capital structure of zero-debt firms can be (should be) analysed.

Last, considering the alternative estimation methods, the estimates of QML logit(4) model and Beta logit differ in few cases. For Portugal, the variable CRISIS in the QML logit(4) model is statistically significant, however, only at 10% significance level. Whereas, in the Beta logit model the variable becomes statistically significant at 5% significance level. In the case of Greece, the variable HIGHTECH is statistically insignificant in the QML logit(4) model. Whereas, in the Beta logit model the variable becomes statistically significant at 5% significance level. Last, in the QML logit(4) model for France, the variables CRISIS and SME are statistically significant at 1% significance levels. By contrast, these variables become statistically insignificant in the Beta logit model. Besides these exceptions, all other significant variables in the QML logit(4) and Beta logit models, appear to be significant at same significance levels with same signs.

Table 3.12: Robustness Tests-Portugal

	FULL SAMPLE			EXCLUDING ZERO-DEBT FIRMS	
VARIABLES	QML logit (1)	QML probit (2)	QML cloglog (3)	QML logit (4)	Beta logit (5)
CRISIS	-0.530***	-0.308***	-0.452***	-0.227*	-0.236**
	(0.139)	(0.082)	(0.115)	(0.136)	(0.119)
HIGHTECH	-0.100	-0.060	-0.076	-0.049	-0.093
	(0.081)	(0.049)	(0.066)	(0.079)	(0.073)
SME	0.160	0.101*	0.127	-0.007	-0.013
	(0.097)	(0.059)	(0.079)	(0.096)	(0.090)
SMECRISIS	0.143	0.071	0.145	0.047	0.079
	(0.140)	(0.083)	(0.116)	(0.137)	(0.121)
GROWTH	0.005***	0.003***	0.003***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SIZE	-0.092***	-0.056***	-0.072***	-0.140***	-0.123***
	(0.007)	(0.004)	(0.005)	(0.006)	(0.006)
PROFITABILITY	-1.191***	-0.731***	-0.827***	-1.414***	-1.257***
	(0.133)	(0.079)	(0.092)	(0.137)	(0.107)
TANGIBILITY	0.971***	0.598***	0.758***	0.794***	0.779***
	(0.048)	(0.029)	(0.038)	(0.045)	(0.042)
LIQUIDITY	-0.822***	-0.501***	-0.661***	-0.542***	-0.479***
	(0.057)	(0.034)	(0.047)	(0.054)	(0.050)
Constant	-0.223*	-0.145**	-0.543***	0.358***	0.250**
	(0.117)	(0.072)	(0.095)	(0.114)	(0.107)
Observations	13,457	13,457	13,457	11,791	11,791

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.13: Robustness Tests-Greece

	FULL SAMPLE			EXCLUDING ZERO-DEBT FIRMS	
VARIABLES	QML logit (1)	QML probit (2)	QML cloglog (3)	QML logit (4)	Beta logit (5)
CRISIS	0.070	0.055	0.051	0.274	0.180
	(0.184)	(0.102)	(0.164)	(0.172)	(0.153)
HIGHTECH	-0.565***	-0.302***	-0.521***	-0.189	-0.263**
	(0.156)	(0.082)	(0.145)	(0.136)	(0.128)
SME	0.126	0.064	0.117	0.058	0.024
	(0.111)	(0.061)	(0.100)	(0.103)	(0.094)
SMECRISIS	0.046	0.010	0.052	-0.134	-0.022
	(0.194)	(0.107)	(0.173)	(0.180)	(0.161)
GROWTH	0.004***	0.002***	0.004***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SIZE	0.216***	0.117***	0.198***	0.005	0.025
	(0.021)	(0.012)	(0.019)	(0.020)	(0.018)
PROFITABILITY	-1.919***	-1.054***	-1.729***	-1.334***	-1.072***
	(0.368)	(0.207)	(0.326)	(0.452)	(0.405)
TANGIBILITY	1.023***	0.566***	0.934***	-0.184	0.145
	(0.156)	(0.085)	(0.142)	(0.153)	(0.130)
LIQUIDITY	-1.256***	-0.627***	-1.194***	-0.988***	-0.621***
	(0.231)	(0.117)	(0.218)	(0.204)	(0.167)
Constant	-3.851***	-2.185***	-3.753***	-0.744***	-1.110***
	(0.229)	(0.125)	(0.208)	(0.222)	(0.195)
Observations	3,800	3,800	3,800	1,880	1,880

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.14: Robustness Tests-France

	FULL SAMPLE			EXCLUDING ZERO-DEBT FIRMS	
VARIABLES	QML logit (1)	QML probit (2)	QML cloglog (3)	QML logit(4)	Beta logit (5)
CRISIS	0.158***	0.093***	0.134***	0.070***	0.010
	(0.023)	(0.013)	(0.020)	(0.022)	(0.019)
HIGHTECH	-0.759***	-0.411***	-0.699***	-0.504***	-0.351***
	(0.038)	(0.020)	(0.036)	(0.037)	(0.030)
SME	0.166***	0.093***	0.148***	0.077***	0.028
	(0.027)	(0.016)	(0.024)	(0.026)	(0.023)
SMECRISIS	-0.063*	-0.035*	-0.054*	0.004	0.046*
	(0.033)	(0.019)	(0.029)	(0.031)	(0.028)
GROWTH	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SIZE	-0.151***	-0.090***	-0.123***	-0.239***	-0.162***
	(0.005)	(0.003)	(0.004)	(0.005)	(0.004)
PROFITABILITY	-0.281***	-0.183***	-0.201***	-0.762***	-0.485***
	(0.056)	(0.034)	(0.045)	(0.067)	(0.055)
TANGIBILITY	1.492***	0.885***	1.255***	0.928***	0.952***
	(0.037)	(0.022)	(0.031)	(0.036)	(0.031)
LIQUIDITY	0.163***	0.084***	0.167***	0.166***	0.084***
	(0.033)	(0.019)	(0.029)	(0.030)	(0.027)
Constant	-0.904***	-0.547***	-1.134***	0.449***	0.032
	(0.044)	(0.026)	(0.038)	(0.046)	(0.037)
Observations	42,219	42,219	42,219	29,751	29,751

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.15: Robustness Tests-Germany

	FULL SAMPLE			EXCLUDING ZERO-DEBT FIRMS	
VARIABLES	QML logit (1)	QML probit (2)	QML cloglog (3)	QML logit (4)	Beta logit (5)
CRISIS	-0.895***	-0.540***	-0.496***	-0.473***	-0.329***
	(0.113)	(0.067)	(0.076)	(0.107)	(0.119)
HIGHTECH	-0.400***	-0.239***	-0.316***	-0.242***	-0.195***
	(0.062)	(0.037)	(0.051)	(0.059)	(0.055)
SME	0.593***	0.348***	0.342***	0.542***	0.500***
	(0.122)	(0.071)	(0.074)	(0.108)	(0.144)
SMECRISIS	-0.927***	-0.551***	-0.619***	-0.785***	-0.645***
	(0.133)	(0.078)	(0.086)	(0.119)	(0.152)
GROWTH	0.004***	0.002***	0.003***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SIZE	-0.170***	-0.102***	-0.120***	-0.144***	-0.149***
	(0.015)	(0.009)	(0.011)	(0.014)	(0.013)
PROFITABILITY	-0.077	-0.050	0.022	0.096	0.001
	(0.104)	(0.065)	(0.074)	(0.145)	(0.121)
TANGIBILITY	1.714***	1.023***	1.272***	0.908***	0.921***
	(0.122)	(0.072)	(0.091)	(0.118)	(0.105)
LIQUIDITY	-1.605***	-0.950***	-1.325***	-1.533***	-1.321***
	(0.163)	(0.094)	(0.136)	(0.156)	(0.137)
Constant	1.203***	0.721***	0.285***	1.336***	1.151***
	(0.145)	(0.085)	(0.099)	(0.136)	(0.149)
Observations	3,069	3,069	3,069	2,303	2,303

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.6 Conclusion

This study uses fractional regression models, where QML logit is considered the main model, to analyze capital structure of manufacturing firms based in Portugal, Greece, France, and Germany. To be specific, this study primarily tries to find answers to the following three questions. First, do High-Tech firms take less debt than Low-Tech firms? Second, how did global financial crisis of 2007-2008 affect capital structure of firms? Third, did SMEs take less debt than large firms in the after-crisis period? Regression results provide answer to all of these questions. First, High-Tech firms in all four countries, on average, take less debt than Low-Tech firms. Second, firms in Portugal and Germany took less debt and firms in France took more debt subsequent to crisis on average. In the case of Greece, the corresponding variable is found to be statistically insignificant. Third, SMEs in France and Germany comparatively took less debt in 2003 than in 2007. For Portugal and Greece, the corresponding variable is found to be statistically insignificant. Besides finding answers to the three questions, this study tries to find how expected growth, size, profitability, tangibility, and liquidity affect capital structure of firms. Regression results provide evidence that in all cases expected growth and tangibility are positively associated with leverage. Profitability, in all cases, is negatively related with leverage. In Portugal, France, and Germany, size affects leverage negatively. Whereas, in Greece, size affects leverage positively. Last, liquidity is negatively related with leverage in the case of Portugal, Greece, and Germany. And, in the case of France, the relationship is positive.

Chapter 4

Application: Analysing Efficiency

This chapter presents another application of fractional regression models, where the aim is to model relationship between DEA efficiency scores and exogenous factors. Rather than moving to the application straightaway, the first section succinctly presents the basic DEA model in addition to the output oriented BCC model, which is utilised in the application, using Cooper, Seiford, and Tone (2006). Then the subsequent sections present the application in a structured manner.

4.1 Data Envelopment Analysis

In data envelopment analysis(DEA), each organization that is under scrutiny is called a DMU(Decision Making Unit). Put another way, a DMU can be refereed as the entity that is responsible for transforming inputs into outputs and whose performances are to be evaluated. For example, DMUs could be farms, companies, banks, hospitals, schools, and so forth.

4.1.1 The CCR Model

Given n DMUs and corresponding data, DEA measures the efficiency of each DMU once and thus needs to solve n linear programs i.e. one for each DMU$_j$. Let the DMU$_j$ to be evaluated on any trial be designated as DMU$_o$ where o ranges from $1, 2, 3, ..., n$. To obtain values for input "weights" (v_i) $(i = 1, ..., m)$ and output "weights" (u_r) $(r = 1, ..., s)$ as variables, the following fractional programming problem, known as the CCR model as it was introduced by Charnes, Cooper, and Rhodes (1978), could be used.

$$(FP_0) \qquad \max_{u,v} \theta = \frac{u_1 y_{1o} + u_2 y_{2o} + ... + u_s y_{so}}{v_1 x_{1o} + v_2 x_{2o} + ... + v_m x_{mo}} \tag{4.1}$$

$$\text{subject to} \qquad \frac{u_1 y_{1j} + u_2 y_{2j} + ... + u_s y_{sj}}{v_1 x_{1j} + v_2 x_{2j} + ... + v_m x_{mj}} \leq 1 \ (j = 1, ..., n) \tag{4.2}$$

$$v_1, v_2, ..., v_m \geq 0 \tag{4.3}$$

$$u_1, u_2, ..., u_s \geq 0 \tag{4.4}$$

The above fractional linear program (FP_0) can be replaced by the following linear program (LP_0), by applying Charnes and Cooper (1962) transformation.

$$(LP_0) \qquad \max_{\mu,v} \theta = \mu_1 y_{1o} + ... + \mu_s y_{so} \tag{4.5}$$

$$\text{subject to} \qquad v_1 x_{1o} + ... + v_m x_{mo} = 1 \tag{4.6}$$

$$\mu_1 y_{1j} + ... + \mu_s y_{sj} \leq v_1 x_{1j} + ... + v_m x_{mj} \quad j = 1, ..., n \tag{4.7}$$

$$v_1, v_2, ..., v_m \geq 0 \tag{4.8}$$

$$\mu_1, \mu_2, ..., \mu_s \geq 0 \tag{4.9}$$

Theoretically, the fractional program(FP_0) is equivalent to (LP_0).

The (LP_0) can be expressed in vector-matrix notation:

$$(LP_0) \qquad \max_{\boldsymbol{u},\boldsymbol{v}} \ \boldsymbol{\mu y_0} \tag{4.10}$$

$$\text{subject to} \qquad \boldsymbol{v x}_0 = 1 \tag{4.11}$$

$$-\boldsymbol{vX} + \boldsymbol{uY} \leq \boldsymbol{0} \tag{4.12}$$

$$\boldsymbol{v}, \boldsymbol{u} \geq \boldsymbol{0}. \tag{4.13}$$

The dual of the (LP_0) can be expressed with a real variable θ and a nonnegative vector $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, ..., \lambda_n)^T$ as follows

$$(DLP_0) \qquad \min_{\boldsymbol{\theta},\boldsymbol{\lambda}} \ \boldsymbol{\theta} \tag{4.14}$$

$$\text{subject to} \qquad \theta \boldsymbol{x}_0 - \boldsymbol{X\lambda} \geq \boldsymbol{0} \tag{4.15}$$

$$\boldsymbol{Y\lambda} \geq \boldsymbol{y}_0 \tag{4.16}$$

$$\boldsymbol{\lambda} \geq \boldsymbol{0}. \tag{4.17}$$

4.1.2 The Output-oriented BCC Model

The BCC model was introduced by Banker, Charnes, and Cooper (1984). The only difference between BCC and CCR models is that an additional constraint is added to the former model. In fact, the added condition is $\sum_{j=1}^{n} \lambda_j = 1$. Alternatively, this can be written as $\boldsymbol{e\lambda} = 1$, where $\boldsymbol{e}$ is a row vector with all elements unity and $\boldsymbol{\lambda}$ is a column vector with all elements non-negative.

The output-oriented BCC model can be written as follows

$$(BCC - O_0) \qquad \max_{\eta_B, \boldsymbol{\lambda}} \ \eta_B \tag{4.18}$$

$$\text{subject to} \qquad \boldsymbol{X\lambda} \leq \boldsymbol{x}_0 \tag{4.19}$$

$$\eta_B \boldsymbol{y}_0 - \boldsymbol{Y\lambda} \leq \boldsymbol{0} \tag{4.20}$$

$$\boldsymbol{e\lambda} = 1 \tag{4.21}$$

$$\boldsymbol{\lambda} \geq 0 \tag{4.22}$$

The above form is known as the envelopment form of the output-oriented BCC model. The dual(multiplier) form the model can be expressed in the following way.

$$\min_{\boldsymbol{v},\boldsymbol{v},v_0} \quad \boldsymbol{v}\boldsymbol{x}_0 - v_0 \tag{4.23}$$

$$\text{subject to} \qquad \boldsymbol{u}\boldsymbol{y}_0 = 1 \tag{4.24}$$

$$\boldsymbol{v}\boldsymbol{X} - \boldsymbol{u}\boldsymbol{Y} - v_0\boldsymbol{e} \geq \boldsymbol{0} \tag{4.25}$$

$$\boldsymbol{v} \geq \boldsymbol{0}, \boldsymbol{u} \geq \boldsymbol{0}, v_0 \text{ free in sign,} \tag{4.26}$$

where v_0 is the scalar associated with $\boldsymbol{e}\boldsymbol{\lambda} = 1$ in the envelopment model.

4.2 Main Hypotheses

This study focuses on the efficiency scores of manufacturing firms in Portugal, Greece, France, and Germany, and tries to analyze them by taking exogenous factors such as economic condition (before and after financial crisis), use of technology (high or low), type of firm (SME or large), and country of origin into account. Given the paucity of empirical research on this particular topic, hypotheses of this study are formulated using pragmatic approach. The four hypotheses are given below:

1. *Firms become more efficient subsequent to financial crisis*: When a financial crisis hits an economy, firms' operations and performances, in general, suffer significantly. To ameliorate such situation, firms become more cautious about their use and allocation of resources. Thus, it is plausible that firms firms become more efficient after the crisis.

2. *High-Tech firms are more efficient than Low-Tech firms*: High-Tech firms, by nature, tend to spend more on research and development (R&D). This implies that, if efficiency of firms varies significantly on the basis of their use of technology, High-Tech firms would be more efficient than Low-Tech firms.

3. *SMEs are less efficient than large firms*: Large firms typically have more available funds to spend on R&D than SMEs. In effect, large firms spend more on R&D and also gain the associated advantage. In other words, large firms, as they spend more R&D, tend to use their resources more efficiently. So, one could argue that SMEs are less efficient than large firms.

4. *Firms in Portugal, France, and Germany are more efficient than firms in Greece*: Political stability, macroeconomic environment, quality of labor force, tax policies, and other related factors significantly affect how firms do their businesses. Moreover, these factors differ country to country. In other words, business environment tends to vary across nations. As a result, a particular type of firm in a given country, for example, will have to operate differently in another country. In the aftermath of financial crisis 2007-2008, Greece faced sovereign debt crisis. And since then the country has been suffering economically and politically. So, it is obvious that business environment there, compared to the other countries, is less favorable. Hence, it is plausible to infer that efficiency of firms in Portugal, France, and Germany are higher than that of Greece.

4.3 The Data

The data source and the data set used in this application are exactly similar to the previous application. In fact, manufacturing firms (High-Tech and Low-Tech) of the same four countries Portugal (PT), Greece (GR), France (FR), and Germany (DE) for the year 2007 and 2013 are considered.

In the first stage of DEA analysis, operating revenue turnover was considered as the only output, and total assets, shareholders' funds, and number of employees were considered as inputs. Assuming variable returns to scale, efficiency scores were then obtained using an output oriented BCC model. In this process, a random sample of 1024 companies, 512 for each year were considered. Moreover, due to the use of super efficiency, some scores exceeded 1. To use FRM in the second stage, these scores were normalized by dividing them by the maximum score. Table 4.1 presents the summary statistics of the first stage DEA. The mean of efficiency scores, SCORES, is 0.201 with minimum being 0.028 and maximum being 1[1]. The standard deviation for SCORES is 0.115, which gives an indication that efficiency scores do not vary significantly. The inputs and outputs, however, have very high standard deviations indicating greater variability. The mean of operating revenue turnover, total assets, and shareholders' funds are respectively 33,562.080, 24,938.228, and 5801.248[2].

Table 4.1: Summary Statistics DEA

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
SCORES	0.201	0.115	0.028	1
Operating Revenue Turnover	33562.080	340668.468	-1027.170	8487000
Total Assets	24938.228	259213.954	6.520	6721000
Shareholders' Funds	5801.248	29381.416	-5677.880	538583.813
Number of Employees	99.948	882.770	1	20930
N		1024		

Table 4.2 presents the frequency distribution of countries. In the sample, roughly 86% of the firms belong to France (50.20%) and Portugal (35.94%). The rest of the firms belong to Germany (8.01%) and Greece (5.86%). Table 4.3 presents summary statistics for the other three exogenous variables, whose definitions were discussed in the previous application. The mean of the variable CRISIS is 0.5, indicating there are equal number of observations for the year 2007 and 2013. The variable HIGHTECH has a very small mean, 0.063, confirming that fewer number of firms in the sample use high technology. Last, the mean of the variable SME is 0.940, indicating that most of firms in the sample belong to SME category.

Table 4.2: Summary Statistics-Country

Country	Freq.	Percent	Cum.
DE	60	5.86	5.86
FR	514	50.20	56.05
GR	82	8.01	64.06
PT	368	35.94	100
Total	1024	100	

Table 4.3: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
CRISIS	0.5	0.5	0	1
HIGHTECH	0.063	0.242	0	1
SME	0.940	0.237	0	1
N		1024		

Figures 4.1-4 present four different kernal density plots of efficiency scores, which are categorized by country, use of technology, type of firms, and crisis-period. All the four plots exhibit a common pattern: plots are right skewed. This particular pattern indicates that most firms, regardless of their categorization,

[1]In the sample there are only 7 firms with SCORES=1
[2] All the units are measured in thousands of euros.

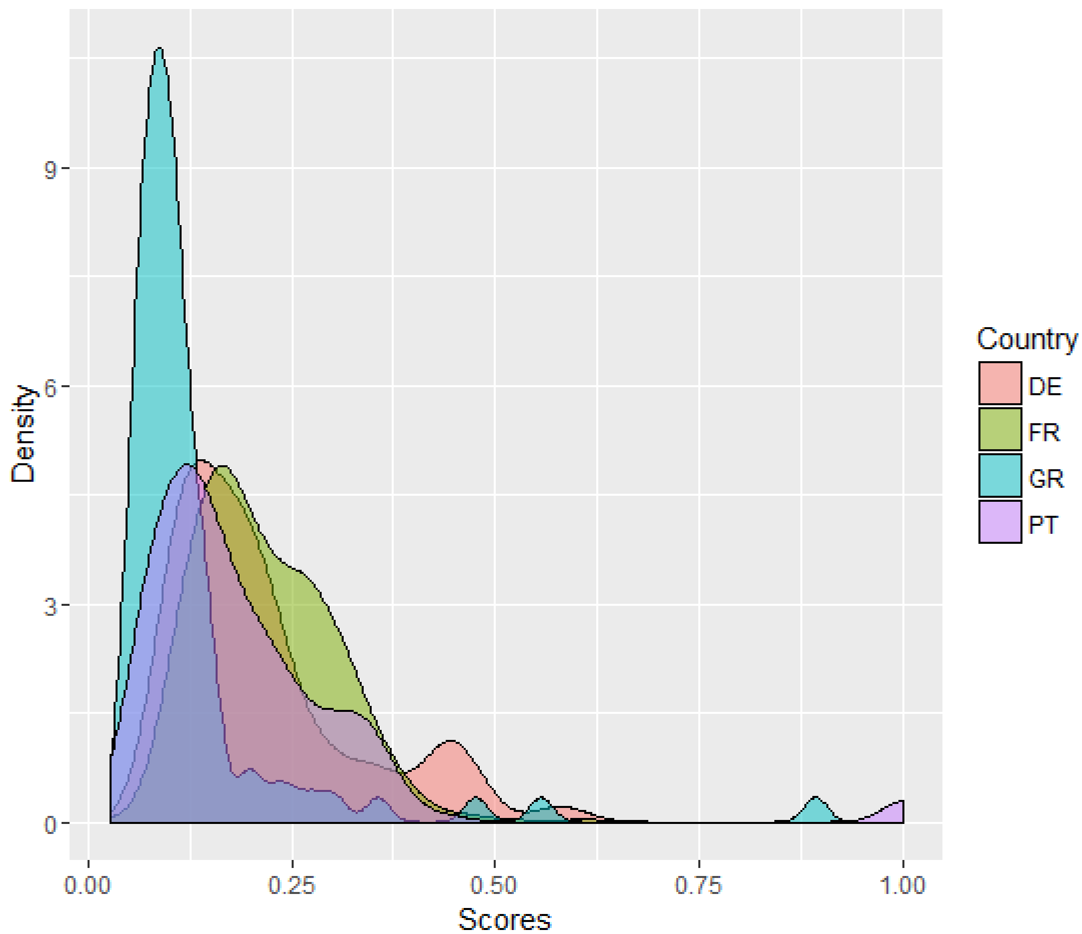

Figure 4.1: Distribution of Scores by Country

have efficiency scores below 50%. Figure 4.1 reveals that firms in Greece are less efficient compared to the firms in other countries. Figure 4.2 shows that efficiency scores of High-Tech and Low-Tech do no vary by much as their distributions look very similar. Figure 4.3 gives an indication that efficiency of SMEs and large firms differ significantly. In fact, density plot for SMEs is more peaked between 0.00 and 0.25 than that of large firms. Moreover, the plot for large firms exhibit a fatter right tail. Overall, these facts hint that large firms are more efficient than SMEs. Last, Figure 4.4 shows that efficiency scores of firms, loosely speaking, do not change before and after financial crisis because the density plots look almost identical.

4.4 Empirical Results

4.4.1 Main Findings

To estimate the QML model, this study primarily considers the logit specification discussed in chapter 2. That is,

$$E(\text{SCORES}|\mathbf{x}) = G(\beta_0 + \beta_1\text{CRISIS} + \beta_2\text{HIGHTECH} + \beta_3\text{SME} + \beta_4\text{DE} + \beta_5\text{FR} + \beta_6\text{PT}), \tag{4.27}$$

where $G(.)$ is the logistic function. Table 4.4 presents the empirical results for the main model obtained from estimating the equation (4.27).

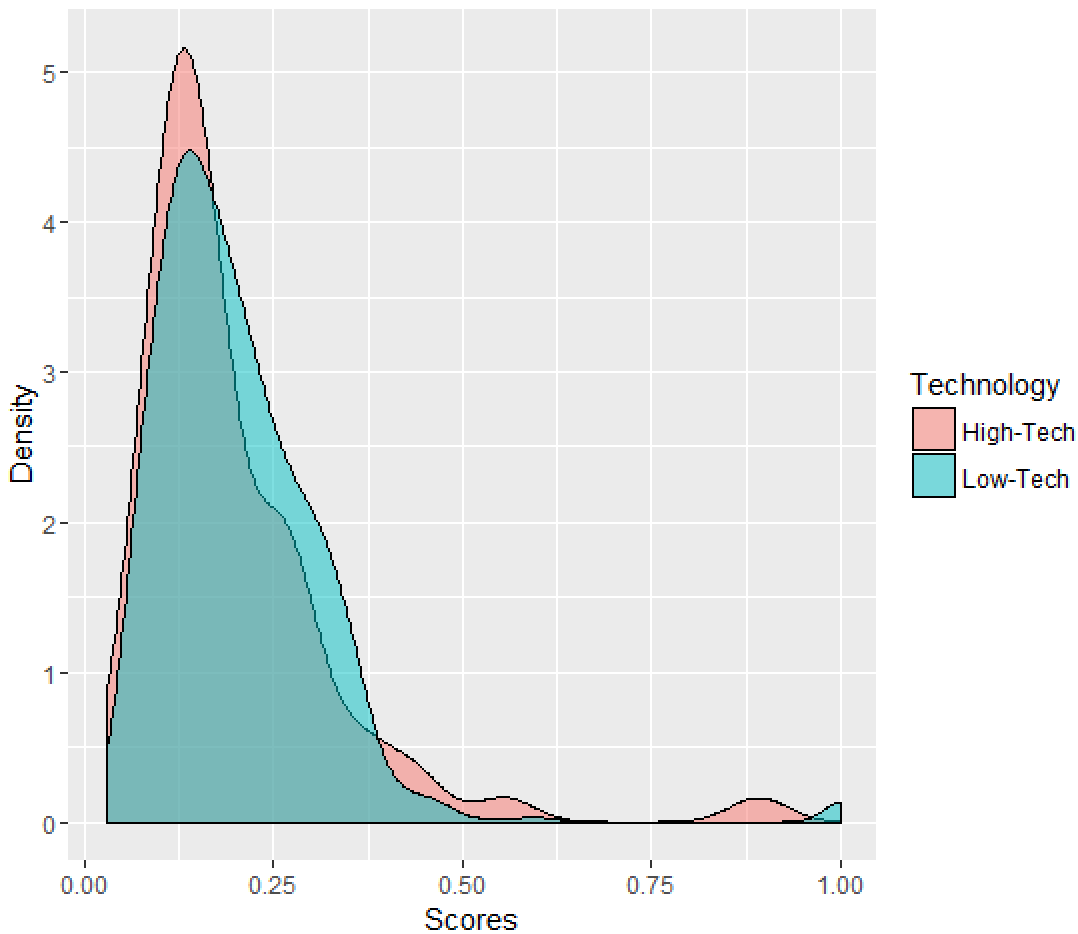

Figure 4.2: Distribution of Scores by Technology

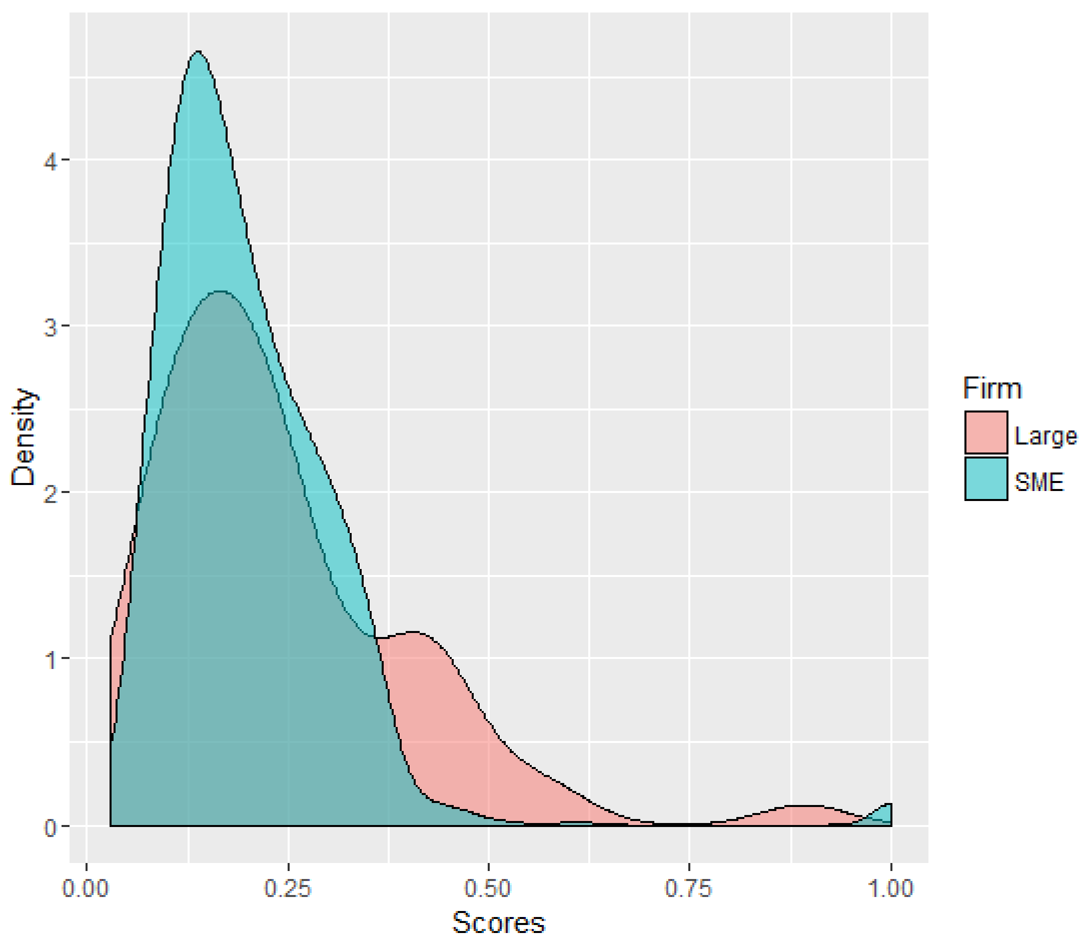

Figure 4.3: Distribution of Scores by type of Firm

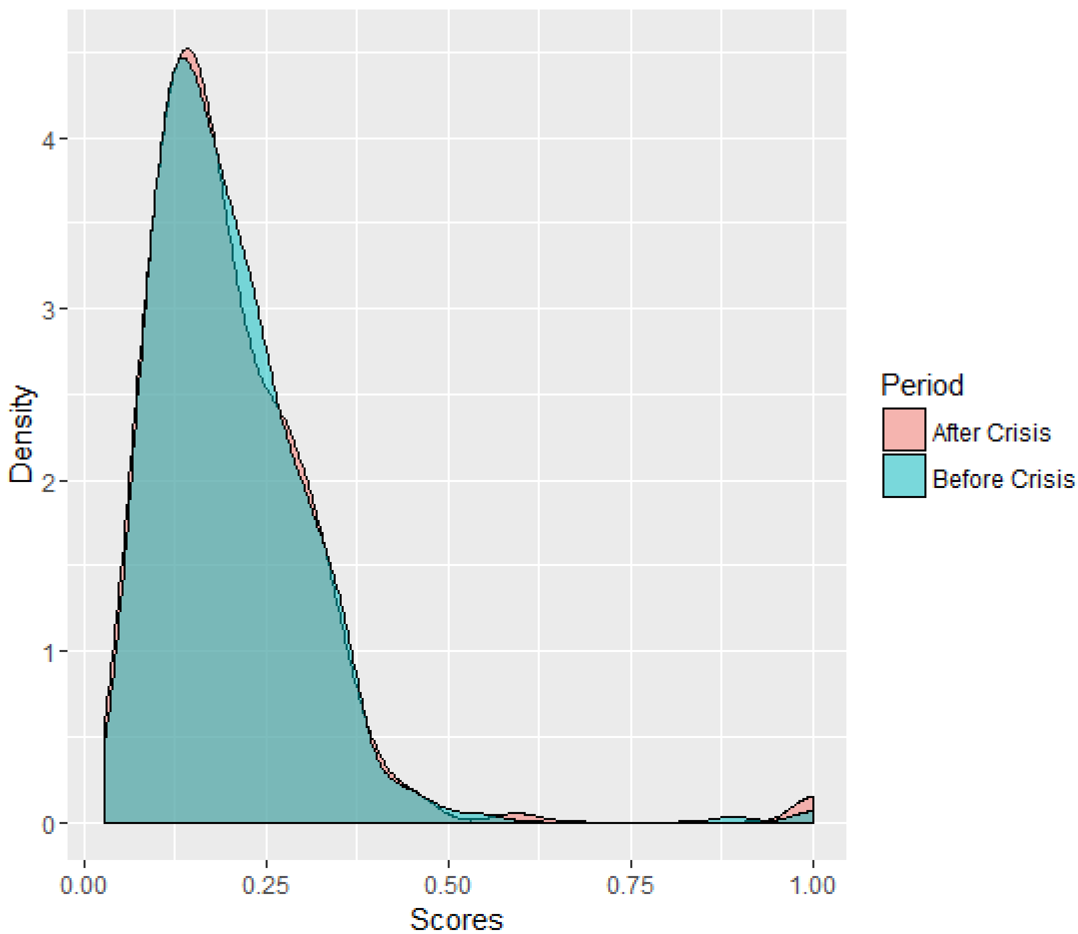

Figure 4.4: Distribution of Scores by Period

The variables CRISIS and HIGHTECH are not statistically significant. That is, financial crisis crisis and use of technology do not play any role in explaining efficiency of manufacturing firms. The variable SME, however, is statistically significant at 10% significance level and the sign of the coefficient is negative as expected. In short, SMEs are less efficient than large firms. Last, the country dummies DE, FR, and PT are statistically significant at 5% significance level, and their coefficients have positive sign. This corroborate the hypothesis that efficiency of firms vary across countries. Moreover, manufacturing firms in Germany, France, and Portugal are more efficient than manufacturing firms in Greece.

Table 4.4: Estimation Results : Main Model (QML Logit)

Variable	**Coefficient**	**(Std. Err.)**
CRISIS	0.007	(0.044)
HIGHTECH	-0.109	(0.109)
SME	-0.269*	(0.116)
DE	0.563**	(0.168)
FR	0.647**	(0.116)
PT	0.489**	(0.120)
Constant	-1.667**	(0.195)

4.5 Robustness Tests

Similar to the first application, this sub-section has three aims. One, to examine whether estimates of a model change significantly when specification for G(·) changes. Two, to find out if the small number of fully-efficient firms i.e. firms with SCORES=1 affect the regression results. Three, to find out whether alternative estimation methods i.e ML and QML produce significantly different results. In doing so, this sub-section first makes the use of two additional models: QML probit and QML cloglog, and compares their results with that of the main model. Then, it employs QML logit model to a new sample which excludes fully-efficient firms, and compares the estimates with that of the main model. Last, this sub-section employs QML logit and Beta logit models to the restricted sample, and compares the results. Tables 3.12-15 present the estimates of the new models for each country. These tables, for the ease of comparison, also include the result of the main model. To avoid confusion, in the discussion of the regression results which follows next, the QML logit for the full sample is referred to as the main model, and the QML logit for the restricted sample is simply referred to as QML logit(4).

Table 4.5 shows that the estimates of the QML models are similar. All the variables that are significant in the main model, remain significant with the same level of significance. Moreover, signs of the coefficients of the explanatory variables remain the same. In short, QML probit, QML cloglog, and the main model provide similar estimates.

The of estimates QML logit model and the main model do not contradict. In fact, the explanatory variables which are significant in the main model, also remain significant in the QML logit model at the same level of significance. Moreover, the coefficients of the variables maintain the same sign across these two models. In short, exclusion of the fully-efficient firms does not bring any change to the regression results.

Last, considering the results of the two different estimation methods applied to the restricted sample, Table 4.6 shows that Beta logit and the main model provide similar estimates except for the variable HIGH-TECH. In the Beta logit model, HIGHTECH is statistically significant at 5% significance level. By contrast, in the QML logit model the variable becomes insignificant. In any case, however, the Beta logit and QML logit do not yield any contradictory estimates in terms of signs.

Table 4.5: Robustness Tests

	FULL SAMPLE			RESTRICTED SAMPLE	
VARIABLES	QML logit (1)	QML probit (2)	QML cloglog (3)	QML logit (4)	Beta logit (5)
CRISIS	0.007	0.003	0.007	-0.024	-0.018
	(0.044)	(0.025)	(0.039)	(0.036)	(0.033)
HIGHTECH	-0.109	-0.060	-0.100	-0.091	-0.141**
	(0.109)	(0.062)	(0.097)	(0.108)	(0.071)
SME	-0.269**	-0.162**	-0.231**	-0.283**	-0.176**
	(0.116)	(0.069)	(0.099)	(0.114)	(0.072)
DE	0.563***	0.311***	0.517***	0.556***	0.581***
	(0.168)	(0.090)	(0.155)	(0.167)	(0.099)
FR	0.647***	0.362***	0.588***	0.647***	0.659***
	(0.116)	(0.060)	(0.110)	(0.115)	(0.071)
PT	0.489***	0.272***	0.447***	0.386***	0.366***
	(0.120)	(0.062)	(0.114)	(0.114)	(0.073)
Constant	-1.667***	-0.986***	-1.770***	-1.639***	-1.734***
	(0.195)	(0.107)	(0.177)	(0.192)	(0.098)
Observations	1,024	1,024	1,024	1,017	1,017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.6 Conclusion

This study uses fractional regression models and present an analysis of efficiency scores of manufacturing firms that are based in Portugal, Greece, France, and Germany. Regression models provide evidence that financial crisis does not affect efficiency of firms. Also, use of technology does not play any role in explaining efficiency of firms. By contrast, efficiency scores of large firms and SMEs differ significantly. In fact, large firms are, on average, more efficient than SMEs. Last, there is sufficient evidence that efficiency of firms varies across countries. Fractional regression models, to be specific, indicate that firms in Portugal, France, and Germany are more efficient than firms in Greece.

Chapter 5

Conclusion

Followed by the introductory chapter of this thesis, Chapter 2 presents fractional regression models. This chapter, in particular, discusses about quasi-maximum likelihood based fractional regression models and maximum likelihood based Beta fractional regression model. Then the following chapters present two applications of these models.

Chapter 3 analyzes capital structure of manufacturing firms of Portugal, Greece, France, and Germany, which either use high technology or low technology. The main finding of this study are as follows. First, High-Tech firms in all four countries, on average, take less debt than Low-Tech firms. Second, global financial crisis of 2008-09 causes firms in Portugal and Germany to take less debt, and firms in France to take more debt. In the case of Greece, the corresponding variable happens to be insignificant. Third, SMEs in France and Germany comparatively take less after the crisis. For Portugal and Greece, the corresponding variable appears to be insignificant.

Chapter 4 analyzes the efficiency scores of the firms, which are obtained using data envelopment analysis. The main findings of this study are as follows. First, financial crisis does not affect efficiency of firms. Second, use of technology does not play any role in explaining efficiency of firms. Third, large firms, on average, are more efficient than SMEs. Last, firms in Portugal, France, and Germany are, on average, more efficient than firms in Greece.

References

Aghion, P., Bond, S., Klemm, A., & Marinescu, I. (2004). Technology and financial structure: are innovative firms different? *Journal of the European Economic Association*, *2*(2-3), 277–288.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, *30*(9), 1078–1092.

Charnes, A., & Cooper, W. W. (1962). Programming with linear fractional functionals. *Naval Research logistics quarterly*, *9*(3-4), 181–186.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429–444.

Cooper, W. W., Seiford, L. M., & Tone, K. (2006). *Introduction to data envelopment analysis and its uses: with dea-solver software and references.* Springer Science & Business Media.

Damodaran, A. (2014). *Applied corporate finance* (4th ed.). John Wiley & Sons.

Ferrari, S., & Cribari-Neto, F. (2004). Beta regression for modelling rates and proportions. *Journal of Applied Statistics*, *31*(7), 799–815.

Fosberg, R. H. (2012). Capital structure and the 2003 tax cuts. *Journal of Business Economics and Finance*, *1*(2), 5–20.

Frank, M. Z., & Goyal, V. K. (2009). Capital structure decisions: which factors are reliably important? *Financial management*, *38*(1), 1–37.

Gertler, M., & Gilchrist, S. (1993). The role of credit market imperfections in the monetary transmission mechanism: arguments and evidence. *The Scandinavian Journal of Economics*, 43–64.

Graham, J., Leary, M. T., & Roberts, M. R. (2014). *How does government borrowing affect corporate financing and investment?* (Tech. Rep.). National Bureau of Economic Research.

Hermalin, B. E., & Wallace, N. E. (1994). The determinants of efficiency and solvency in savings and loans. *The RAND Journal of Economics*, 361–381.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, *3*(4), 305–360.

Kraus, A., & Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *The journal of finance*, *28*(4), 911–922.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of financial economics*, *5*(2), 147–175.

Myers, S. C. (1984). The capital structure puzzle. *The journal of finance*, *39*(3), 574–592.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, *13*(2), 187–221.

Paolino, P. (2001). Maximum likelihood estimation of models with beta-distributed dependent variables. *Political Analysis*, *9*(4), 325–346.

Papke, L. E., & Wooldridge, J. (1996). *Econometric methods for fractional response variables with an application to 401 (k) plan participation rates.* National Bureau of Economic Research Cambridge, Mass., USA.

Ramalho, E. A., Ramalho, J. J. S., & Murteira, J. M. R. (2011). Alternative estimating and testing empirical strategies for fractional regression models. *Journal of Economic Surveys*, *25*(1), 19–68.

Ramalho, J. J. S., & Silva, J. V. (2009). A two-part fractional regression model for the financial leverage decisions of micro, small, medium and large firms. *Quantitative Finance*, *9*(5), 621–636.

Shyam-Sunder, L., & Myers, S. C. (1999). Testing static tradeoff against pecking order models of capital structure. *Journal of financial economics*, *51*(2), 219–244.

Strebulaev, I. A., & Yang, B. (2013). The mystery of zero-leverage firms. *Journal of Financial Economics*, *109*(1), 1–23.

Warner, J. B. (1977). Bankruptcy, absolute priority, and the pricing of risky debt claims. *Journal of Financial Economics*, *4*(3), 239–276.