Journal of
Risk and Financial Management

Article

Efficiency and Determinants of Capital Structure in the Greek Pharmaceutical, Cosmetic and Detergent Industries

Ioannis E. Tsolas

School of Applied Mathematical and Physical Sciences, National Technical University of Athens, 15780 Athens, Greece; itsolas@central.ntua.gr

Abstract: The purpose of this paper is to investigate the relationship between a firm's capital structure (i.e., leverage) and its operating environment, taking into account firm (i.e., efficiency, asset structure, profitability, size, age and risk) and industry effects. For a sample of Greek pharmaceutical, cosmetic and detergent (PCD) enterprises, firm efficiency was estimated using bootstrapped data envelopment analysis (DEA), and a leverage model was produced using ordinary least squares (OLS) regression. The findings confirm the significance of firm efficiency (i.e., the franchise-value hypothesis over the efficiency-risk hypothesis) and asset structure on leverage. Efficiency and overall and short-term leverage have a significant negative relationship, indicating that more efficient firms tend to choose a relatively low debt ratio. Pharma firms are more affected since they are less efficient than cosmetics and detergents firms. Furthermore, asset structure and short- and long- term leverage have a significant negative and positive relationship, respectively, indicating that the firms with more tangible assets have less short-term debt and more long-term debt in their capital structure. Cosmetic and detergent firms, which have slightly more tangible assets than pharma firms, appear to be able to substitute high-cost, short-term debt with the low-cost, long-term debt by using such assets as collateral.

Keywords: capital structure; firm efficiency; data envelopment analysis (DEA); pharmaceutical, cosmetic and detergent (PCD) firms; Greece

check for updates

Citation: Tsolas, Ioannis E.. 2021. Efficiency and Determinants of Capital Structure in the Greek Pharmaceutical, Cosmetic and Detergent Industries. *Journal of Risk and Financial Management* 14: 579. https://doi.org/10.3390/jrfm14120579

Academic Editor: Ştefan Cristian Gherghina

Received: 30 October 2021
Accepted: 24 November 2021
Published: 2 December 2021

1. Introduction

The capital structure of a firm refers to the amount of debt and/or equity used to fund operations and finance assets. Firms are looking for an optimum capital structure to ensure a lower cost of capital and, as a result, higher profitability. Several theories have been offered to address the various problems that firms have faced in this regard. Numerous hypotheses tested in the related literature support the challenge of providing a single capital structure mix for each industry. Many of the factors assumed to influence capital structure are either not clearly quantitative or impossible to measure, which is a major problem for researchers (Margaritis and Psillaki 2007).

The efficiency-risk and the franchise-value hypotheses (Berger and Patti 2006; Margaritis and Psillaki 2007, 2010) were tested in this study to analyze the impact of firms' technical efficiency on financial leverage that is used as a capital structure metric. The terms operational and financial leverage are used interchangeably. Fixed debt costs are tied to financial leverage, whereas fixed operational costs are linked to operational leverage (Dakua 2019).

According to the efficiency-risk hypothesis, efficient firms choose lower equity ratios than others because efficiency reduces the expected cost of bankruptcy and financial distress. Higher efficiency leads to higher expected returns of a given capital structure, and moreover, it substitutes equity to some extent to protect the firm from future crises. According to the franchise-value hypothesis, more efficient firms choose higher equity ratios to protect the economic rents or franchise value associated with higher efficiency from the possibility of liquidation (Berger and Patti 2006). Therefore, under the efficiency-risk and franchise-value hypotheses, firms with higher efficiency ratings and hence lower potential risks of bankruptcy and financial distress may choose higher and lower debt-to-equity ratios, respectively (Margaritis and Psillaki 2007).

Frontier-based inefficiency, also referred to as X-inefficiency (Berger and Patti 2006) or technical inefficiency, as proposed initially by Leibenstein (1966), is defined as a failure to reach the efficient production frontier (Margaritis and Psillaki 2007). Competitive frontier-based approaches such as the parametric stochastic frontier analysis (SFA) (Aigner et al. 1977; Meeusen and Broeck 1977) and the non-parametric data envelopment analysis (DEA) (Charnes et al. 1978) are used to evaluate firm performance. SFA involves the econometric estimation of error term elements such as statistical noise and inefficiency, as well as the choice of a functional form of production (or cost) function. DEA is an operations research method used to calculate the efficiency of a sample of entities (e.g., firms) known as decision-making units (DMUs).

The DEA-based efficiency used in the current study demonstrates how well a firm generates profits from its different sources of capital. Efficiency ranges from zero to one, and only the units with efficiency scores of one are included in the efficiency (best-practice) frontier. DEA determines the efficient frontier by considering the optimal relationship between inputs and outputs, as well as the efficient DMUs that optimize this relationship. The ambiguity surrounding DEA rating estimates is not taken into account; therefore, any variation from the frontier is considered to be attributable to inefficiency in traditional DEA applications. There is uncertainty in DEA due to sample variability or frontier estimation, which can lead to biased DEA (point) estimations and thus incorrect conclusions. The bootstrap method (Efron 1982; Efron and Tibshirani 1993) is used to correct the calculated efficiency and produce bias-corrected efficiency (Simar and Wilson 1998, 2000a, 2000b).

The current study aims to investigate whether DEA-bootstrapped firm efficiency and selected firm-specific factors are important in capital structure decisions for a sample of Greek pharmaceutical, cosmetic and detergent (PCD) firms. Moreover, the industry effect on leverage is also investigated. PCD firms in Greece are considered a broader sector, see, e.g., Pirounakis (1997). Pharmaceuticals are seen as an industry with substantial export potential, which will help to boost the Greek economy. The pharmaceutical industry in Greece is one of the most competitive in the manufacturing sector, and it is an important element of the Greek economy (Kounnou and Kyrkilis 2020). Face, body and hair products, as well as fragrances, are the most important segments in the cosmetics industry. The manufacturing of various detergents, as well as aromatic and non-aromatic soaps in liquid and solid form, are the most important segments in the detergents industry. The purpose of this paper is to develop a leverage model by regressing leverage on DEA-bootstrapped efficiency and some other control variables.

The remainder of this paper is organized as follows: Section 2 reviews current research on capital structure and firm performance. In Section 3, the conceptual framework, methodology and data set are described. Section 4 summarizes and discusses the findings. Section 5 concludes the paper.

2. Literature Review

Capital structure is one of the most fascinating business problems, and top management and scholars are still trying to figure out the best mix of debt and equity to optimize firm value and boost investors' profits. While there has been comprehensive empirical research on capital structure, there is no universal agreement on the best debt-to-equity ratio (Vermoesen et al. 2013).

The vast majority of previous research has concentrated on identifying the factors that affect firm capital structure. To describe the impact of each firm factor on capital structure, two contrasting theories, the pecking order theory (POT) and the trade-off theory (TOT), have been proposed. The POT is based on the presence of asymmetric information between managers and investors, and according to this theory, no firm has an ideal capital structure. Instead, companies tend to fund their operations with funding sources that have the least amount of asymmetric information, since borrowing costs are positively related to borrower information. As a result, companies prioritize their corporate financial decisions in a hierarchical order, with internal funds coming first, then debt, and eventually new equity as a last resort. The TOT claims that each firm has an optimal capital structure. This is accomplished by using an extra unit of debt to strike a balance between costs and benefits. The degree of leverage increases these costs.

In recent years, researchers have focused their attention on capital structure and firm performance using frontier methods to measure firm efficiency. Among the notable studies, there are DEA (Margaritis and Psillaki 2007, 2010; Mok et al. 2007; Seelanatha 2010; Kapelko and Lansink 2015; She and Guo 2018; Fernandes et al. 2018; Gadanakis et al. 2020) and SFA works (Weill 2008; Cheng and Tzeng 2011; Hanousek et al. 2015; Shaik 2015; Guo et al. 2021).

Firm efficiency was used as a surrogate for firm performance by Margaritis and Psillaki (2007, 2010). They investigated the bi-directional relationship between DEA-based performance and capital structure through empirical analysis. Mok et al. (2007) used Tobit regression to evaluate the impact of leverage on DEA-based efficiency for a sample of Chinese toy manufacturing enterprises. Seelanatha (2010) investigated the effects of firm efficiency, market share and industry concentration on capital structure. Kapelko and Lansink (2015) used bootstrapped DEA to estimate the efficiency of Spanish construction enterprises, and then bootstrap-truncated regression to find efficiency determinants such as leverage and other factors. She and Guo (2018) studied a sample of global e-retail firms using panel data and found them to be consistent with POT, a negative relationship between firm performance and leverage. Fernandes et al. (2018) analyzed the bi-directional relationship between technical efficiency and capital structure for a sample of Portuguese small-sized enterprises. Gadanakis et al. (2020) used double-bootstrapped DEA to investigate the relationship between efficiency and capital structure for the Italian cereal farms.

Weill (2008) investigated the relationship between leverage and corporate performance by using a stochastic cost frontier model. Cheng and Tzeng (2011) employed SFA to measure the efficiency of Taiwan manufacturing enterprises and then applied regression to techniques to examine the bi-directional relationship between leverage and efficiency. (Hanousek et al. 2015) employed SFA, and they studied factors, including leverage, that affect corporate efficiency in Europe. Shaik (2015) investigated the effect of debt risk on firm inefficiency and productivity using SFA. Guo et al. (2021) estimated firm efficiency using SFA in order to investigate the capital structure—firm performance nexus. They showed that different levels of debt financing have a different impact on corporate efficiency.

This research contributes in two ways. First, it investigated the role of profit generation and cost decisions in determining the extent of firm leverage. To do so, DEA was used to build a link between efficiency and capital structure, as well as to derive firm ratings based on how efficient their capital structure is. In particular, a DEA-bootstrapped technique was employed to measure technical efficiency, in contrast to most prior relevant DEA research, which lacked estimates of firm efficiencies' uncertainty. Second, the current study contributes to the corpus of knowledge by showing that DEA-based efficiency is an important factor in capital structure decisions.

3. Methods

3.1. Conceptual Framework

Firms can employ their assets with varied levels of managerial expertise, which is reflected in technical efficiency (Farrell 1957). A firm's technical efficiency is regarded as a performance metric, and DEA may be used to calculate it. A firm is technically efficient if it achieves high levels of net earnings before taxes without wasting financial resources (i.e., equity, and short- and long-term liabilities). The DEA model used in this study is based on

Harrison and Rouse (2016) "*Funding Efficiency Model*", and the efficiency ratings produced show how well firms maximize their return on investment.

The current work used a two-stage modeling methodology. A DEA model was employed in the first stage to measure firm technical efficiency. For instance, if a company delivers monetary outcomes (net profit before taxes) with the least number of total assets, it is considered efficient in attaining its objectives. The objective of the second stage was to regress leverage on DEA-based efficiency and some other control variables and thus provide a leverage model for a group of Greek PCD firms. In order to investigate whether efficiency is a determinant of leverage, the following hypotheses were formed:

Hypothesis 1 (H1). *The efficiency-risk hypothesis, i.e., efficiency has a positive effect on leverage;*

Hypothesis 2 (H2). *The franchise-value hypothesis, i.e., the effect of efficiency on leverage is negative.*

Two-stage DEA is a modeling tool that employs DEA to obtain efficiency ratings and then employs regression techniques such as Tobit and ordinary least squares (OLS) to investigate the impact of leverage and other firm-specific characteristics on DEA efficiency ratings. Instead of Tobit regression, Simar and Wilson (2007) recommended using an integrated with bootstrapping-truncated regression. They bootstrapped the efficiency ratings to generate bias-corrected efficiency scores and then used bootstrapped-truncated regression to regress these corrected efficiency scores on control variables. Many studies are interested in determining which regression approach is the most suitable to use. The interested reader is directed to Liu et al. (2016) for a recent review.

Another issue with two-stage DEA is the separation of the space of the DEA input–output variables from the space of the control variables. Simar and Wilson (2007) found that Tobit and OLS were ineffective and proposed bootstrapped-truncated regression, despite the fact that this technique could have the same flaw. According to Daraio et al. (2018), if the separability condition for the DEA input–output and control variables is not met, the second stage findings will have disadvantages. The separability assumption of Simar and Wilson (2007) is strong, and it is unlikely to be satisfied in real-world applications (Banker et al. 2019). Therefore, in the current paper the reverse hypothesis, i.e., leverage is a determinant of efficiency, is not investigated.

3.2. Model Building

3.2.1. DEA Modeling

The BCC variable returns to scale model (Banker et al. 1984) was adopted to account for scale effects because the sample contains firms of various sizes. In terms of model orientation, efficiency is calculated by either minimizing inputs or increasing outputs. Input-oriented models estimate the largest possible reduction in inputs for given outputs, whereas output-oriented models estimate the highest possible increase in outputs for a given quantity of inputs.

For a group of n firms, $j = 1, \ldots, n$ that use inputs $X \in \Re^{m}{}_{+}$ to generate outputs $Y \in \Re^{rk}{}_{+}$, the BCC input-oriented Model (1) (Cooper et al. 2007) is employed to quantify the relative technical efficiency of sample firms:

$$
\begin{gathered}
Min\theta \\
\text{subject to} \\
\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{ij_0} \\
\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj_0} \\
\sum_{j=1}^{n} \lambda_j = 1 \\
\lambda_j \geq 0, j = 1, 2, \cdots, n, i = 1, 2, \ldots m,\ r = 1, 2, \ldots, k
\end{gathered} \tag{1}
$$

where x_{ij} is the ith input used by the jth firm; y_{rj} is the rth output produced by the jth firm; θ signifies the efficiency score of firm "$_0$"; "$_0$" stands for the firm that is being assessed; and λ_j indicates the contribution of firm j in the computation of efficiency of firm "$_0$".

Model (1)'s optimal solution gives the firm "$_0$" an efficiency score. The model looks for a weighted by λ_j sum of firm outputs that is higher than firm's "$_0$" output and a weighted by λ_j sum of firm inputs that is lower than firm's "$_0$" input. For each firm, the model-solving technique is repeated, and firms with $\theta^* = 1$ and $\theta^* < 1$ are deemed efficient and inefficient, respectively. In the current study the derived efficiency ratings produced by Model (1) are bias-corrected by means of bootstrap (Simar and Wilson 1998, 2000a, 2000b).

3.2.2. The Leverage Model

The leverage model used to evaluate hypotheses H1 and H2 relates firm's leverage as a capital structure metric to firm's bootstrapped DEA-based performance as well as a range of other variables that have been found to be associated with leverage in the literature (see Margaritis and Psillaki 2007). The leverage equation is given by:

$$L_i = \beta_0 + \beta_1 TE_i + \beta_2\, z_2 + v_i \tag{2}$$

where L_i is the firm leverage ratio, z_2 is a vector of factors other than technical efficiency (TE), and v_i is an error term. Under the efficiency-risk hypothesis, i.e., $\beta_1 > 0$, efficiency has a positive influence on leverage, whereas under the franchise-value hypothesis, i.e., $\beta_1 < 0$, efficiency has a negative influence on leverage.

The leverage model in this study uses three capital structure metrics as dependent variables: overall leverage (OL), i.e., the ratio of total liabilities to total assets, short-term leverage (STL), i.e., the ratio of short-term liabilities to total assets, and long-term leverage (LTL), i.e., the ratio of long-term liabilities to total assets; see also Kuč and Kaličanin (2021).

Firm size, asset tangibility, profitability, age of company and risk are the other firm-specific factors besides TE. Moreover, an industry dummy variable is used to capture the unobservable industry variant impact on leverage. The logarithm of a company's revenue (sales) is used to calculate its size. Size is expected to be positively related to leverage according to TOT since larger enterprises are more diversified and fail less frequently than smaller enterprises (Fernandes et al. 2018).

The ratio of fixed tangible to total assets is used to calculate asset tangibility (TANG). Because of asymmetric information and agency costs, lenders may be compelled to require assurances in the form of collateral. As a result, asset tangibility is assumed to be positively linked to debt (Fernandes et al. 2018).

Profitability (PROF) is determined by the ratio of pre-tax net income to total assets. On the impact of profitability on leverage, there are contradictory theoretical predictions. According to POT, profitability should be negatively associated with leverage, since profitable companies would finance their investments with internal funds first, and then turn to external financing when internal funding is inadequate. Because the most profitable companies have larger debt potential and can benefit from debt tax-shields, TOT can predict a positive association between profitability and leverage (Fernandes et al. 2018).

The age of the company is a crucial factor in measuring debt repayment and risk-taking behavior in terms of capital structure. In reality, the year a company was formed and how long it has been in service decide its age; in the current study the logarithm of age was used. When it comes to leverage and firm age, empirical research paints a mixed image. According to the TOT, age is a key determinant of a firm's reliability, and a positive relationship is predicted. Firms, according to the POT, keep their payment over time. Therefore, older firms have a considerable amount of accumulated retained earnings and depend less on external financing to complete their financial compliance than younger companies (Shil et al. 2019).

Risk is a term that refers to the possibility of failure and the potential loss of earnings, and it plays a significant role in capital structure. Risk tends to be inversely proportional to leverage, according to finance theory. A firm with a high risk of losing money is more likely to go bankrupt and has less borrowing capacity (Shil et al. 2019). Risk, i.e., earnings variability measured as the logarithm of the standard deviation of the firm's net operating income over a 3-year period is expected to be negatively related to leverage, according to TOT (Sbeti and Moosa 2012).

3.3. Data Set

For the purposes of this study, thirty-eight PCD firms were evaluated. Twenty-two out of thirty-eight firms (58% of the total) are pharmaceuticals, eleven firms (29% of the total) are in the cosmetic industry and the remained firms (13% of the total) are in the detergent industry. Companies in the sample had financial statement data accessible between 2015 and 2017. The selected firms were evaluated by DEA to measure their performance based on the accounting data of 2017. In the first stage, the equity and short- and long-term liabilities were used as inputs, whereas net earnings before taxes was the only output. In the second stage, the firm-specific variables, except for the DEA-based efficiency, are: SIZE, which is the logarithm of sales, asset tangibility (TANG = net fixed assets/total assets), profitability (PROF = net earnings before taxes/total assets), AGE, which is the logarithm of the age of the firm, and RISK, which is the logarithm of the 3-year standard deviation of net earnings before taxes over the 2015–2017 period.

The descriptive statistics for the variables in the DEA assessment are shown in Table 1.

Table 1. Greek PCD firms: Descriptive statistics of DEA input–output variables ('000 Euros).

DEA Inputs–Output	DEA Inputs			DEA Output
Descriptive Statistics	**Equity**	**Short-Term Liabilities**	**Long-Term Liabilities**	**Net Earnings before Taxes**
Mean	21,271.74	26,968.65	12,238.60	2003.32
Standard deviation	27,246.78	42,960.74	20,708.45	5785.89
Median	12,728.29	13,154.87	3788.96	417.44
Min	33.43	1.64	8.29	−9938.19
Max	132,043.00	232,138.99	99,107.30	22,862.77

The sample firms are listed in Appendix A.

4. Results

The DEA Model (1) was employed in the first stage of analysis to estimate the technical efficiency of Greek PCD firms for the year 2017. Then, using bootstrap, the DEA efficiency scores of the firms were corrected for the bias. The bias-corrected scores were used to investigate the relationship between technical efficiency and leverage and to test the H1 and H2 hypotheses. The Model (1) was used to calculate each company's technical efficiency in minimizing equity and short- and long-term liabilities and achieving the observed earnings (i.e., net earnings before taxes). Inefficiencies account for the distance between each firm and the efficient frontier. By using statistical inference derived from the bootstrapping technique, these efficiency estimates provide insight into future improvements. The DEA efficiency calculations were corrected for bias using 2000 bootstrap samples. Table 2 summarizes results for the point (technical) efficiency, bias-corrected efficiency, and bias.

Table 2. Results (mean, standard deviation) of bias, original and bootstrapped efficiency estimates.

Estimates	Original (Point) Efficiency (%)	Bias-Corrected Efficiency (%)	Bias (%)
All firms			
Mean	40.68	28.23	12.46
Standard deviation	39.32	27.21	19.07
Pharma firms			
Mean	30.79	23.71	7.08
Standard deviation	30.54	22.31	8.90
Cosmetics-Detergents firms			
Mean	54.28	34.44	19.85
Standard deviation	46.55	32.53	26.19

Full efficiency = 100%.

As demonstrated by bias-corrected efficiencies, the magnitude of the corrected efficiencies is much lower than the point (i.e., original) efficiencies, with reduced dispersion. Because they offer a more accurate picture of the underlying efficiency, bias-corrected performance figures are favored over original efficiencies. The mean bias-corrected efficiency for all PCB firms is about 28%, indicating that each company should reduce their current financial resources by 72%, on average, achieving the current level of revenues. In comparison to pharmaceutical firms, cosmetic and detergent firms are more efficient.

The cross-efficiency method (Sexton et al. 1986) was also employed to validate the implementation of Model (1). The equivalent dual model of the BCC Model (1) focuses on self-evaluation using the model's optimal weights, whereas cross-efficiency is based on peer-evaluation using weights generated by evaluating each of the sample firms. Cooper et al. (2011) provide a detailed description of the cross-efficiency method for interested readers. The mean cross-efficiency is in-between the mean point and mean bias-corrected efficiency provided by Model (1) (mean cross-efficiency for all PCB firms: 36.50%). The cross-efficiency standard deviation (22.04 percent) is smaller than the point and bias-corrected efficiency standard deviations. For pharma and cosmetics-detergents companies, the mean cross-efficiency (and standard deviation) is 34.18% (20.38%) and 39.68% (24.46%), respectively. Detailed results are available from the author upon request. The ranking of firms does not indicate substantial variations in performance because Spearman's rank correlation coefficient between the bootstrapped and cross efficiency estimates is 0.70.

The OLS regression Model (2) was employed, which intends to examine efficiency as well as other variables as determinants of (overall, short-term, and long-term) leverage. Table 3 shows the descriptive statistics for the control variables, except for efficiency.

Table 4 summarizes the findings of the OLS regression Model (2). The OLS findings show a significant negative relationship between performance and both OL and STL ratios, supporting the franchise-value hypothesis over the efficiency-risk hypothesis. More efficient enterprises, according to the franchise-value hypothesis, tend to have more equity resources on hand; therefore, they choose lower debt levels to protect their potential earnings or franchise value, all other things being equal. Cosmetics and detergents companies appear to be more efficient (mean bias-corrected efficiency: 34.44%, mean cross efficiency: 39.68%) and choose lower debt levels (OL: 54.20%, STL: 35.40%) than pharmaceutical companies (mean bias-corrected efficiency: 23.71%, mean cross efficiency: 34,18%, OL: 58%, STL: 42.63%). The findings supporting the franchise-value hypothesis are consistent with those of Margaritis and Psillaki (2007) and Seelanatha (2010). Efficiency has a positive but insignificant effect on LTL ratio. It is worth mentioning that the average LTL ratio (16.81%) for PCB manufacturers is significantly lower than the average OL (56.40%) and STL (39.59%) ratios.

Table 3. Descriptive statistics of selected control variables.

Descriptive Statistics	OL (%)	LTL (%)	STL (%)	TANG (%)	PROF (%)	SIZE	AGE	RISK
All firms								
Mean	56.40	16.81	39.59	39.16	−0.14	16.57	3.30	13.22
Standard deviation	20.05	14.90	20.30	24.40	15.24	2.07	0.95	1.84
Median	58.62	12.29	42.56	38.37	1.82	17.15	3.77	13.58
Min	10.16	0.79	0.70	0.17	−65.76	8.98	0.69	8.15
Max	89.07	50.27	87.31	86.30	28.92	19.30	4.41	15.70
Pharma firms								
Mean	58.00	15.37	42.63	38.58	−2.07	38.55	3.30	13.23
Standard deviation	21.45	15.36	20.52	25.85	16.63	20.55	1.10	1.60
Median	59.10	9.60	44.27	38.92	1.82	45.50	3.82	13.58
Min	11.79	0.79	10.03	0.17	−65.76	2.00	0.69	9.79
Max	89.07	50.27	87.31	71.24	18.19	67.00	4.20	15.64
Cosmetics–Detergents firms								
Mean	54.20	18.80	35.40	39.95	2.52	33.44	3.31	13.22
Standard deviation	18.39	14.49	19.88	23.05	13.15	19.79	0.73	2.17
Median	54.51	17.46	37.68	38.37	2.23	27.50	3.31	13.56
Min	10.16	0.88	0.70	3.93	−26.45	4.00	1.39	8.15
Max	75.86	45.70	65.99	84.75	28.92	82.00	4.41	15.70

OL: Overall leverage; LTL: Long-term leverage; STL: Short-term leverage; TANG = Net fixed assets/total assets; PROF = Net earnings before taxes/total assets; SIZE = Ln(Sales); AGE: The logarithm of the number of years since the firm was founded; RISK: The logarithm of the 3-year standard deviation of net earnings before taxes over the 2015–2017 period.

Table 4. Leverage model: Results of the OLS regression.

Variable	Coefficient	Standard Error	t-Value	(p-Value)
Dependent variable: OL				
Intercept	0.418	0.3511	1.19	0.243
TE	−0.291	0.1460	−1.99	0.055
TANG	−0.142	0.1321	−1.07	0.291
PROF	0.375	0.2304	1.63	0.114
SIZE	0.048	0.0294	1.62	0.115
AGE	−0.047	0.0372	−1.27	0.215
RISK	−0.027	0.0316	−0.84	0.408
R-squared = 0.35				
Dependent variable: LTL				
Intercept	−0.072	0.2696	−0.27	0.791
TE	0.040	0.1121	0.36	0.721
TANG	0.361	0.1015	3.56	0.001
PROF	0.201	0.1770	1.13	0.265
SIZE	0.015	0.0226	0.67	0.506
AGE	−0.015	0.0286	−0.51	0.614
RISK	−0.009	0.0243	−0.36	0.720
R-squared = 0.31				
Dependent variable: STL				
Intercept	0.490	0.2968	1.65	0.109
TE	−0.332	0.1235	−2.69	0.012
TANG	−0.503	0.1117	−4.50	0.000
PROF	0.174	0.1948	0.89	0.379
SIZE	0.033	0.0249	1.31	0.200
AGE	−0.033	0.0315	−1.04	0.308
RISK	−0.018	0.0267	−0.66	0.512
R-squared = 0.55				

OL: Overall leverage; LTL: Long-term leverage; STL: Short-term leverage; TE: Bias-corrected technical efficiency; TANG = Net fixed assets/total assets; PROF = Net earnings before taxes/total assets; SIZE = Ln(Sales); AGE: The logarithm of the number of years since the firm was founded; RISK: The logarithm of the 3-year standard deviation of net earnings before taxes over the 2015–2017 period; Number of obs. = 38.

The ratio of tangible (net fixed) assets to total assets is positively and substantially related to LTL ratio since tangible assets serve as a proxy for collateral. Both OL and STL ratios are negatively impacted by the ratio of tangible assets to total assets, but only STL is significantly affected. The current research supports both theoretical predictions by documenting statistically significant positive and negative coefficients for variables used to represent asset tangibility with LTL and STL ratios. These results are consistent with those of Seelanatha (2010). It is worth noticing that the average fixed tangible asset to total asset ratio does not differ much between pharma (38.58%) and cosmetic and detergent companies (39.95%).

All leverage metrics are positively, though not substantially, related to profitability, which contradicts the POT's expectations but is consistent with the TOT (Margaritis and Psillaki 2007). According to this theory, more profitable firms would raise their ideal debt-to-equity ratio because higher profitability lowers the risk of bankruptcy and financial distress associated with higher debt levels. It is worth noticing that the average profitability is lower in the pharma industry (−2.07%) compared to the cosmetic and detergent industry (2.52%). Firm size, as measured by the logarithm of sales, has a positive but insignificant impact on all leverage ratios. The firm's age, which is measured by the logarithm as the number of years after incorporation, has a negative but insignificant effect on all leverage ratios. The final explanatory variable is risk (i.e., earnings variability), which is negatively but not significantly related to all leverage metrics, according to TOT. In regard to the AGE and RISK variables, there are no substantial differences between pharma and cosmetic and detergent firms.

In order to test the results showed in Table 4, the cross-efficiency ratings were used instead of bias-corrected technical efficiency, but the findings were insignificant for almost all the explanatory variables.

Another OLS regression was performed incorporating a dummy variable to capture the unobservable industry variant impact on leverage. No evidence found to support the industry (i.e., pharmaceuticals, cosmetic and detergent) variant impact on leverage. The results are available upon request from the author. The signs for the estimated coefficients for the other control variables are to the same as the results presented in Table 4.

5. Conclusions

The current study adopted a two-stage modelling approach to investigate the relationship between firm efficiency and a range of other factors on capital structure (i.e., leverage) for a group of Greek PCD firms. Through the bootstrapped-DEA method, firm ratings reflect their relative efficient capital structure. The use of bootstrap provides the estimation of more robust efficiency scores and improves on the majority of most of the previous studies. Then, an attempt was made to explain how leverage ratios are influenced by efficiency as well as by other variables.

The following are the most important conclusions of the study: More efficient firms have a lower level of corporate leverage supporting the franchise value hypothesis, and they pick lower overall and short-term leverage ratios to safeguard their future revenue or franchise value. The pharma firms are mostly affected, as they are more inefficient compared to cosmetic and detergent firms. The firms with more tangible assets have more long-term debt and fewer short-term debt in their capital structure. The cosmetic and detergent firms with a slightly greater level of tangible assets compared to pharma firms seem to be able to substitute high-cost, short-term debt with the low-cost long-term debt by using such assets as collateral.

More profitable firms are able to increase their optimum debt-to-equity ratio because higher profitability reduces the potential costs of bankruptcy and financial distress associated with higher debt, assuming all other factors remain constant**.** The cosmetic and detergent firms that are more profitable compared to pharma firms seem to have the advantage of increasing their optimum debt-to-equity ratio.

Data gathering for the current study began three years before, and it is necessary to analyze the study's findings in light of the COVID-19 crisis. It seems only fitting, then, to wrap up the analysis with some musings on what the pandemic means for the financial structure of the companies studied. COVID restrictions have boosted revenues for huge tech firms such as pharmaceutical firms, while damaging or bankrupting numerous smaller firms that rely on the old economy (Levy 2020; Golubeva 2021). Furthermore, intellectual property rights may protect pharma companies' intangible assets for long periods of time (Baines and Hager 2021). Many companies in the cosmetics business will need to find new sources of funding as a result of the COVID-19 crisis, which has caused severe harm to their financial sheets. Although mergers and acquisitions are projected to increase, multiples may drop from pre-crisis levels (see also Gerstell et al. 2020). As for the detergent industry, due to the increase in demand for chemical materials such as detergents, their trend is expected to be higher than the general trend of the products of other sectors.

This study is useful for policy makers, regulators and investors because it provides evidence that sample firms are being deterred by high leverage due to low efficiency ratings. This is the case for the sample pharma firms as they are more inefficient compared to cosmetic and detergent firms. The cosmetic and detergent firms could take advantage of the slightly greater level of tangible assets compared to pharma firms and substitute high-cost, short-term debt with the low-cost long-term debt by using such assets as collateral. Moreover, the sample cosmetic detergent firms, as more profitable firms, can increase their optimal debt-to-equity ratio.

There are some limitations of the current research. Sample size can be questioned with regard to the number of firms and the years included in the data. The firms in the sample must have at least three years of data in order to measure earnings variability, and the choice of the three-year period requires a compromise between the number of firms that can be included in the study and the availability of sufficient firm-specific data. Although three years of data are used, adding additional years may provide an opportunity to expand the analysis. The current study can be seen as a first approach and as basis for future research on the determinants of the capital structure of the Greek PCB firms. It can be extended in the future to study a longer time period and also investigate the effects of the COVID-19 crisis.

In terms of future research directions, the study could benefit from a longer time period analysis to see whether capital structure is related to dynamic DEA-based metrics and lagged values of selected control variables and investigate the effects of the COVID-19 crisis. Moreover, although this study examines firm and industry effects on capital structure decisions for Greek PCD companies, macroeconomic factors may also be included in the analysis and therefore, the researchers wishing to continue the line of research in this article could consider factors such as interest rates and gross domestic product (GDP) in their future research.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the author.

Acknowledgments: The author would like to thank two anonymous reviewers for their useful comments and suggestions.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

The sample PCD firms are listed in Table A1.

Table A1. List of sample firms.

No.	Firms
Pharmaceuticals industry	
1	Abbvie Pharmaceuticals S.A.
2	Anfarm Hellas S.A.
3	Boehringer Ingelheim Hellas S.A.
4	Bristol Myers Squibb
5	Cooper S.A.
6	Demo S.A.
7	Doctum Pharmaceutical K. Giokaris & Co. S.A.
8	Elpen Pharmaceutical Co. Inc. S.A.
9	Galenica S.A.
10	Genepharm S.A.
11	Gerolymatos International S.A.
12	Innovis Pharma
13	Lavipharm S.A.
14	Nephroclinic S.A.
15	One Pharma Industrial Pharmaceutical S.A.
16	Pharmathen Industrial S.A.
17	Pharmathen International S.A.
18	Servier Hellas Pharmaceutique Ltd.
19	Simvis Pharmaceuticals S.A.
20	Uni-Pharma S.A. Pharmaceutical Laboratories
21	Vianex S.A.
22	Vioser Parenteral Solution Industry S.A.
Cosmetics industry	
1	Apivita S.A.
2	Bodyfarm Hellas S.A.
3	Farcom S.A.
4	Farmeco S.A. Dermcosmetics
5	Fresh Formula S.A.
6	Frezyderm S.A.
7	Gr. Sarantis S.A.
8	Hellenica S.A.
9	Korres Natural Products S.A.
10	Prodis S.A.
11	Zest Natural Cosmetics
Detergents industry	
1	Cleanway Ltd.
2	De Lux Kontelis
3	Eureka Hellas S.A.
4	Papoutsanis S.A.
5	Rolco Vianil S.A.

References

Aigner, Dennis J., Charles Albert Knox Lovell, and Peter Schmidt. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6: 21–37. [CrossRef]

Baines, Joseph, and Sandy B. Hager. 2021. The great debt divergence and its implications for the covid-19 crisis: Mapping corporate leverage as power. *New Political Economy* 26: 885–901. [CrossRef]

Banker, Rajiv D., Abrahim Charnes, and William W. Cooper. 1984. Models for estimating technical and scale efficiencies in Data Envelopment Analysis. *Management Science* 30: 1078–92. [CrossRef]

Banker, Rajiv D., Ram Natarajan, and Daqun Zhang. 2019. Two-stage estimation of the impact of contextual variables in stochastic frontier production function models using Data Envelopment Analysis: Second stage OLS versus bootstrap approaches. *European Journal of Operational Research* 278: 368–84. [CrossRef]

Berger, Allen N., and Emilia Bonaccorsi di Patti. 2006. Capital structure and firm performance: A new approach to testing agency theory and an application to the banking industry. *Journal of Banking and Finance* 30: 1065–102. [CrossRef]

Charnes, Abraham, William W. Cooper, and Edwardo Rhodes. 1978. Measuring the efficiency of decision making units. *European Journal of Operational Research* 2: 429–44. [CrossRef]

Cheng, Ming-Chang, and Zuwei-Ching Tzeng. 2011. Does leverage and efficiency affect each other. *Journal of Accounting, Finance and Economics* 1: 77–95.

Cooper, William W., Lawrence M. Seiford, and Karou Tone. 2007. *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. New York: Springer Science+Business Media, Inc.

Cooper, William W., José L. Ruiz, and Inmaculada Sirvent. 2011. Choices and uses of DEA weights. In *Handbook on Data Envelopment Analysis*, 2nd ed. International Series in Operations Research & Management Science. Edited by William W. Cooper, Lawrence M. Seiford and Joe Zhu. New York: Springer Science+Business Media, Inc., pp. 93–126.

Dakua, Sarada. 2019. Effect of determinants on financial leverage in Indian steel industry: A study on capital structure. *International Journal of Finance & Economics* 24: 427–36.

Daraio, Cinzia, Simar Leopold, and Paul W. Wilson. 2018. Central limit theorems for conditional efficiency measures and tests of the 'separability' condition in non-parametric, two-stage models of production. *The Econometrics Journal* 21: 170–91. [CrossRef]

Efron, Brandley. 1982. *The Jackknife, the Bootstrap, and Other Resampling Plans*. Philadelphia: Society for Industrial and Applied Mathematics Philadelphia.

Efron, Brandley, and Robert J. Tibshirani. 1993. *An Introduction to the Bootstrap*. New York: Chapman & Hall.

Farrell, Michael J. 1957. The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society, Series A (General)* 120: 253–81. [CrossRef]

Fernandes, António, Clara B. Vaz, and Ana Paula Monte. 2018. Efficiency and capital structure in Portuguese SMEs. In *Operational Research. APDIO 2017. Springer Proceedings in Mathematics & Statistics*. Edited by A. Ismael F. Vaz, João Paulo Almeida, José Fernando Oliveira and Alberto Adrego Pinto. Cham: Springer, vol. 223.

Gadanakis, Yiorgos, Gianluca Stefani, Ginerva Virginia Lombardi, and Marco Tiberti. 2020. The impact of financial leverage on farm technical efficiency during periods of price instability. *Agricultural Finance Review* 80: 1–21. [CrossRef]

Gerstell, Emily, Sophie Marchessou, Jennifer Schmidt, and Emma Spagnuolo. 2020. How COVID-19 Is Changing the World of Beauty, McKinsey and Company. Available online: www.mckinsey.com/industries/consumer-packaged-goods/our-insights/how-covid-19-is-changing-the-world-of-beauty# (accessed on 20 November 2021).

Golubeva, Olga. 2021. Firms' performance during the COVID-19 outbreak: International evidence from 13 countries. *Corporate Governance* 21: 1011–27. [CrossRef]

Guo, Haifeng, Tenkir Seifu Legesse, Jiqiang Tang, and Zhen Wu. 2021. Financial leverage and firm efficiency: The mediating role of cash holding. *Applied Economics* 53: 2108–24. [CrossRef]

Hanousek, Jan, Evžen Kočendac, and Anastasiya Shamshur. 2015. Corporate efficiency in Europe. *Journal of Corporate Finance* 32: 24–40. [CrossRef]

Harrison, Julie, and Paul Rouse. 2016. DEA and accounting performance measurement. In *Handbook of Operations Analytics Using Data Envelopment Analysis*. Edited by Shiuh-Nan Hwang, Hsuan-Shih Lee and Joe Zhu. New York: Springer Science+Business Media, pp. 385–412.

Kapelko, Magdalena, and Alfons Oude Lansink. 2015. Technical efficiency and its determinants in the Spanish construction sector pre- and post-financial crisis. *International Journal of Strategic Property Management* 19: 96–109. [CrossRef]

Kounnou, Vasiliki, and Dimitrios Kyrkilis. 2020. Competitiveness, profitability and R/D intensity: The case of the domestic pharmaceutical industry in Greece. In *Business Performance and Financial Institutions in Europe. Business Models and Value Creation across European Industries*. Edited by Alexandra Horobet, Persefoni Polychronidou and Anastasios Karasavvoglou. Cham: Springer Nature Switzerland AG, pp. 47–55.

Kuč, Vukašin, and Đorđe Kaličanin. 2021. Determinants of the capital structure of large companies: Evidence from Serbia. *Economic Research-Ekonomska Istraživanja* 34: 590–607. [CrossRef]

Leibenstein, Harvey. 1966. Allocative Efficiency vs. 'X-Efficiency'. *American Economic Review* 56: 392–415.

Levy, David L. 2020. COVID-19 and global governance. *Journal of Management Studies*, 1–5. [CrossRef]

Liu, John S., Louis Y. Y. Lu, and Wen-Min Lu. 2016. Research fronts in data envelopment analysis. *Omega* 58: 33–45. [CrossRef]

Margaritis, Dimitris, and Maria Psillaki. 2007. Capital structure and firm efficiency. *Journal of Business Finance and Accounting* 34: 1447–69. [CrossRef]

Margaritis, Dimitris, and Maria Psillaki. 2010. Capital structure, equity ownership and firm performance. *Journal of Banking and Finance* 34: 621–32. [CrossRef]

Meeusen, Wim I., and Julien Van Den Broeck. 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review* 18: 435–44. [CrossRef]

Mok, Vincent, Godfrey Yeung, Zhaozhou Han, and Zongzhang Li. 2007. Leverage, technical efficiency and profitability: An application of DEA to foreign-invested toy manufacturing firms in China. *Journal of Contemporary China* 16: 259–74. [CrossRef]

Pirounakis, Nicholas G. 1997. *The Greek Economy: Past, Present and Future*. London: Macmillan.

Sbeti, Wafaa M., and Imad Moosa. 2012. Firm-specific factors as determinants of capital structure in the absence of taxes. *Applied Financial Economics* 22: 209–13. [CrossRef]

Seelanatha, Senarath Lalithananda. 2010. Determinants of capital structure: Further evidence from China. *Economics, Management, and Financial Markets* 5: 106–26.

Sexton, Thomas R., Richard H. Silkman, and Andrew J. Hogan. 1986. Data Envelopment Analysis: Critique and Extensions. In *Measuring Efficiency: An Assessment of Data Envelopment Analysis*. New Directions for Program Evaluation. Edited by Richard H. Silkman. San Francisco: Jossey-Bass, pp. 73–105.

Shaik, Saleem. 2015. Impact of liquidity risk on variations in efficiency and productivity: A panel gamma simulated maximum likelihood estimation. *European Journal of Operational Research* 245: 463–69. [CrossRef]

She, Rui, and Jingzhi Guo. 2018. Capital structure and firm performance: Empirical research based on global e-retailing companies. Paper Presented at the 15th International Conference on e-Business Engineering (ICEBE), Xi'an, China, October 12–14; pp. 251–56.

Shil, Nikhil, Md. Nazmul Hossain, and Md. Nayamot Ullah. 2019. Exploring the underlying factors affecting capital structure decision: A quantitative analysis. *Journal of Corporate Accounting & Finance* 30: 69–84.

Simar, Leopold, and Paul W. Wilson. 1998. Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science* 44: 49–61. [CrossRef]

Simar, Leopold, and Paul W. Wilson. 2000a. A general methodology for bootstrapping in nonparametric frontier models. *Journal of Applied Statistics* 27: 779–802. [CrossRef]

Simar, Leopold, and Paul W. Wilson. 2000b. Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis* 13: 49–78. [CrossRef]

Simar, Leopold, and Paul W. Wilson. 2007. Estimation and inference in two-stage, semi-parametric models of productive processes. *Journal of Econometrics* 136: 31–64. [CrossRef]

Vermoesen, Veronique, Marc Deloof, and Eddy Laveren. 2013. Long-term debt maturity and financing constraints of SMEs during the global financial crisis. *Small Business Economics* 41: 433–48. [CrossRef]

Weill, Laurent. 2008. Leverage and corporate performance: Does institutional environment matter? *Small Business Economics* 30: 251–65. [CrossRef]