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Tutor: Ricardo F. Reis

LEASING'S IMPACT ON FIRM CREDIT RATINGS

By Thomas Bennett - 152111055

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Abstract

By applying two of the most accurate credit rating models, Altman's Z score and Emery and Cogger's Lambda, I have been able to set up a framework for comparing small Portuguese companies with larger FTSE corporations. These two credit rating models have been used in this paper as proxies for a firms stability and overall success. In addition to calculating individual firm credit ratings, I have also obtained cross sectional data on firm leasing intensities which I have used as the independent variables in a number of regression analyses. By regressing the credit rating outputs on the cross sectional leasing data, I have been able to establish whether leasing bears any impact on a firms credit rating.

1) Introduction

Firm credit ratings are among the most reliable indicators of a companies' financial stability and have a tangible impact upon the financial strategy a company chooses to employ. By indirectly affecting the cost of external financing through banks credit terms, a companies' credit rating will dictate the order of 'financing hierarchies' (Frazzani, 1987, p. 1), which in turn influence the financing decisions companies make. In the last decade there has been extensive dialogue surrounding the risk management practices of banks and the incompetence that lead to the financial crisis. The resulting governmental regulation on banks has been overwhelming and has ultimately created a much more diligent financial climate. I will reserve passing judgement on whether or not this is beneficial for the economy at large, though unarguably regulation on banks has made accessing external finance in the Eurozone much more difficult than before 2008. In the context of this forbidding financial climate, it is relevant to conduct enquiries into the mechanics of credit ratings, and to speculate upon how companies could form strategy to improve their credit position. In this thesis, I have isolated leasing intensity as an independent variable and conducted several lines of regression analysis to gain an impression of its impact on company credit ratings.

Leasing bears substantial consequences for company cash flow positions, depreciation expenses and asset flexibility among other things. For this reason, it is fair to ask whether the impact leasing has on firm performance can be mapped out in company credit ratings. Admittedly however, leasing represents but one of the many managerial tools that may adjust a firms credit position. For this and several other reasons, one might expect leasing to have a negligible impact on firm credit ratings. It is this predisposition that I will look to validate over the course of this paper through the use of regression analysis, proceeding with some direction from existing literature which I summarise in my literature review.

It should be noted however, that whilst there has been extensive academic literature produced on the topic of firm growth, and the spectrum of variables that influence it, I have yet to find analysis that specifically addresses the impact of leasing on firm success. Despite this, the body of research surrounding firm's decisions to use leasing, as well as related research on the impact of financing, in a broader sense, on firm success is very relevant to this topic and has influenced the direction of my research.

The central issue this paper looks to address is whether firms are sensitive to differences in leasing intensity over time. Whilst previous literature on firm *cash flow* sensitivity has indicated that larger firms are less vulnerable to variations in cash flow than small firms, they do not identify specific sources of financing which can be used to explain relative success among small and large firms. Nonetheless, the observation that larger firms are less sensitive to fluctuations in cash flow is significant and has formed the bulk of my hypothesis. Broadly, this proposes that differences in leasing intensity have little effect on the success of large firms, though it may be significant for small firms.

The remainder of this thesis is organized as follows: In the next section I review the existing literature which I have found relevant to this topic. I then go on to form my hypothesis on the back of this literature. Beyond forming my hypothesis, I describe the models I have used on the data sets, my methodology and provide some descriptive statistics on the data sets themselves. Finally, I have presented my results and offered some concluding remarks on the trends posited by the regression analysis.

2) Literature Review

In this section I intend to provide a broad synopsis of the articles I have found particularly relevant to this topic, and to indicate how they might direct the formation of my hypothesis.

I have already mentioned that I have yet to find literature pertaining to the relationship between leasing and credit ratings per se, though there is certainly a wealth of literature on related topics. Before entering into detailed discussion on the articles I have found more relevant to this discourse, I should like to briefly highlight the categories into which existing academic research falls under.

Firstly, the largest body of literature I have found discussing the practical implications of leasing is most adequately framed under '*the relationship between leasing and debt*'. Slotty (2009) for example provide a reasoned discussion as to why financially constrained firms use a higher intensity of leasing, suggesting it is to mitigate the agency costs incurred by other forms of financing. This is a theme that has certainly been carried through multiple academic papers on the topic. Sharpe and Nguyen (1995) again provide further evidence of higher leasing intensities among cash constrained firms, offering reinforced support for the view that these firms might reduce the cost of extending debt through leasing.

Perhaps the most interesting study within this field is Eisfelt and Rampini's (2005) article "*Leasing, Ability to repossess and Debt Capacity*" where the authors point to a number of interesting external conditions effecting the ability to repossess, something which subsequently feeds into the risk the lessor is exposed to.

The second category under which there exists a huge body of research is '*the relationship between debt and bankruptcy*'. Debt is invariably incorporated into any model attempting to predict the probability of default among firms. It is definitively the firms' ability to cover its debt that renders it bankrupt or solvent. Thus the *level* of debt as a proportion of assets is always of interest when predicting probabilities of bankruptcy. Halpern, Kieschnick, Rotenberg (2009) for example look at the defining characteristics of bankruptcy cases through observing Highly Leveraged Transactions

[HLTs] over time. They conclude that the debt *composition* is critical in determining whether an HLT goes bankrupt. Specifically, they find that HLT's using public debt are more inclined to go bankrupt or face financial difficulties.

Wu, Gaunt and Grey (2010) also fit into this category, providing an interesting comparison of different prediction models. After assessing a list of models they confirm that *"firms are more likely to experience bankruptcy if they have … high market-based leverage – total liabilities to the market value of total assets"* (Y. Wu, 2010, p. 45).

Finally, the category of research for which I have found very limited material falls under '*the relationship between leasing and bankruptcy*'. This represents a much more focused view on the cause of bankruptcy and has, to my knowledge, been scarcely written about. Perhaps the most common thread of research relating bankruptcy, or more generally the riskiness of firms, to their leasing activity is in previous attempts to derive leasing valuation models. Grenadier (1996) Derives one such model to determine the equilibrium credit spread on leases subject to default risk. The model is but one of several examples of lease contract valuation where a variety of leasing structures and lessee types can be incorporated. This is not the first attempt to provide valuation models for leasing and bears some relevant material pertaining to the inherent risk of leasing assets. However the paper falls short of providing any empirical support for its model and, more importantly, doesn't go as far as to suggest the relationship between previous leasing usage and the valuation of future lease contracts.

This relationship between leasing and credit worthiness is essentially what I am looking to contribute to through studying the effects of variations in leasing intensity on firm credit ratings. The purpose of this paper is really to provide a focused enquiry into an area that several articles would at least suggest an answer to. Oliveira and Fortunato (2006) for example show that smaller and younger firms have higher growth cash flow sensitivities than larger and more mature firms (Oliveira, 2006). This is consistent with a wider body of literature supporting the view that financial constraints on firm growth may be relatively more severe for small and young firms.

This observation follows on from Frazzani, Hubbard and Petersen's 1988 article, "*Financing Constraints and Corporate Investment*" where the authors concentrate on establishing whether information asymmetries regarding cash flows create so called "*financing hierarchies*" (Frazzani, 1987, p. 1). This is a list of financing sources companies use with preference given to the cheapest ones. The authors maintain that in a perfect capital market with no information asymmetries, there is no cost differential between internal and external financing. However, when one introduces a world of imperfect knowledge, investors begin to require a higher premium, making external financing relatively more expensive, thereby creating a financing hierarchy. The central argument can be succinctly summarised as follows;

> "*For young firms with short track records, the probability of purchasing shares of a lemon is undoubtedly high – as firms mature, information asymmetries diminish and the lemons discount rate falls*" (Frazzani, 1987, p. 5)

Lemmon's refer to firms who's assets are overvalued, something the authors approximate using 'Tobin's q'.

The over-riding impression given by Oliveira and Fortunato and Frazzani, Hubbard and Petersen is that access to external financing is more constrained for smaller firms with a shorter track record of paying back loans. Frazzani, Hubbard and Petersen go on to show that investment is in fact "*excessively sensitive*" to cash flow fluctuations among small firms. That firm growth is strongly related to successful investment I will assume is axiomatically true. Subsequently, both articles seem to point to the conclusion that small and young firm's growth is more sensitive to fluctuations in cash flow. That is to say, the rate at which a firm grows as a consequence of gaining access to financing, which in turn improves a firms' short term cash flow position, is negatively correlated to the size and age of the firm.

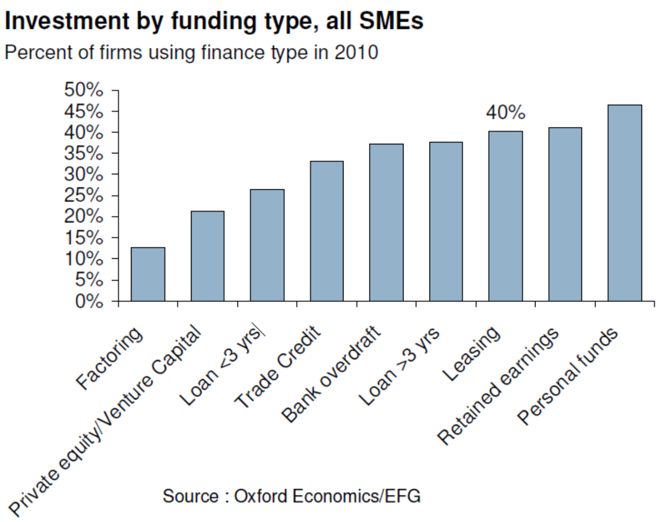
Thorsten Beck, Demirguc-Kunt, Laeven and Levine (2008), in their paper "*Finance, Firm Size and Growth*" continue this line of research, showing further evidence of the sensitivity of smaller, younger firms to financing. Specifically, they analyse cross-industry data where the inter-industry average firm sizes' vary. The perspective of this paper is slightly more removed and leads to a more general conclusion about the effect of the sophistication of economic and financial resources on industry. Again, the idea that the level of access to financing effects' smaller firms' more than large ones is consistent with the authors results. Chiefly, they find that "*small-firm industries grow faster in economies with better developed financial intermediaries*" (Thorsten Beck, 2004)

These conclusions provide a relevant context in which to speculate upon the effect of leasing on firm growth and, more broadly, firm success. Leasing, by providing an alternative to issuing shares or other forms of debt such as loans, represents another conduit to securing investments. Its implications for corporate tax, depreciation and short term cash flow mean that many firms, especially cash constrained ones, resort to leasing to finance their assets. The determinants of corporate leasing policy have been the subject of a wealth of academic research and one could digress into a number of investigations with a view to explaining variations in leasing behaviour between firms. For the sake of formulating my hypothesis, it will suffice to say that smaller firms, whose access to other forms of financing is restricted, tend to rely on leasing more heavily than larger firms, who's reputation in capital markets and among banks is more established.

3) Hypothesis

In their survey of almost 3000 Small to Medium sized Enterprises [SME's] throughout Europe, Oxford Economics' report 'The Use of Leasing Among European SME's' show that Leasing is unquestionably the most popular source of external financing among small firms in Europe. Their survey shows that around 40% of all SME's in their data set use leasing to fund investments, the same proportion of those who use Retained Earnings and only slightly less than those who use Personal Funds.

Figure 1



(Oxford Economics, 2011, p. 6)

Whilst similar research has yet to be conducted for larger firms, it is reasonable to assume that they are less dependent on leasing to secure investment, especially if one considers the suggestions put forth by the literature presented in the previous section. Having said that, it is entirely possible that a similar, if not greater proportion of large firms in Europe will still use leasing to finance assets. The central question is whether the *difference* in the intensity of leasing has any bearing upon their financial success.

In light of the existing academic literature I have reviewed in the previous section, it is natural to arrive at the following logical structure;

1. Small firms are more sensitive than large firms to variations in cash flow.

2. Accessing funds is generally harder for smaller, younger firms.

3. Leasing represents a viable source of financing for smaller, younger firms.

Therefore;

H1. Leasing is likely to have a greater effect on the growth and cash flow position of small firms compared to large firms.

This hypothesis relies on proposition three being valid. Subsequently, although it is not central to the research I conduct in this paper, I feel it is necessary to briefly clarify why leasing represents a more attractive form of financing than equity or debt.

One prominent feature of leasing that justifies this proposition is that leasing allows the lessor to retain ownership of the asset. The important implication of this is that the risk to the lessor is reduced as there is a claim on the asset should the lessee default on payments. Thus leasing allows SME's to finance up to *"100% of the purchase price of an asset, without having to offer any supplementary guarantees of collateral"* (Oxford Economics, 2011, p. 8)

In addition to this, leasing grants companies more flexibility by allowing them to spread payments for a list of assets over a period of time, as well as allowing them to change the types of assets they use more easily. For young and small companies, such flexibility can be very useful, especially given uncertainties over future revenues and how their organisation will operate. It is important to point out that flexible asset management leads to greater control over working capital, something that again is incredibly important for smaller entities. Having a relatively large pool of liquid assets means that companies' who incur unexpected payment obligations, or investment opportunities, are able to meet these requirements, or take advantage of the opportunities when they occur.

The importance of leasing in cash flow management has been shown to be a primary reason for its use among SME's across Europe. Again Oxford Economics' report proves insightful here by stating that *"While no single reason stands out particularly, the* *competitive price of leasing relative to other forms of financing was ranked most important by SME's. The cash flow benefits of leasing are also consistently valued across industrial sectors."* (Oxford Economics, 2011, p. 8).

Further evidence from the survey shows that those SME's that use leasing more intensely tend to benefit from higher growth. The reason for this is intuitive; leasing allows you to invest in assets whilst maintaining higher working capital and retained earnings for further investment.

Whilst the benefits of leasing do extend to larger, more established firms, I believe the extent of the benefit is much less noticeable. This is partly due to their capacity to borrow against a larger value of assets. Thus, if new opportunities for investment do arise, large firms will be able to release more debt to take advantage of this. Furthermore, the relative cost of other forms of financing will be much lower given the fact that larger firms benefit from a track record with which to estimate an interest rate suitable for the level of risk the firm represents.

Perhaps the most important observation to make with regard to larger firms is that their growth opportunities are arguably more limited, and cannot be realised simply by accessing debt. This is an extension of the point made in Frazzani, Hubbard and Petersen's article. They mention that small firms are much more sensitive to changes in cash flow than large firms. I suspect that one reason for this is that the growth opportunities for smaller firms can be realised simply through accessing the cash necessary for capital investment, whereas driving significant growth with a company that has already established itself in the market requires much more than simply investing in new assets. Indeed, the list of companies that have been driven to failure through investing in inefficient assets is extensive. It stands to reason therefore, that growth for large firms is dependent on much more than just accessing cash, but a plethora of other managerial and external factors.

My second hypothesis therefore is;

H2: Whilst leasing does provide cash flow benefits to large corporations, its impact is much less noticeable and does not have a significant effect on a firm's success.

4) Variable Descriptions

Firm success is a rather subjective term, something that can be measured against what one feels is important when analysing a firms overall financial position. Often, analysts will look at various multiples measuring asset efficiency, and more generally the capacity of a firm to generate cash. Whilst this is a well-established line of conduct, using a number of different multiples can make interpretation of results more complex. Often, insights will be gained through considering the multiples in unison, and drawing some sort of indication of where the results are pointing. However, due to the fact that company's accounting data on Bloomberg can contain omissions, I have sought to use a model that encompasses a range of accounting data in one metric. For this, I have found models used in credit rating to be most appropriate.

Credit rating models typically try to establish a companies' probability of default over a given time horizon. In reality, no one credit rating model is used to asses a firms likelihood of default as each one has a degree of inaccuracy inbuilt. In an effort to obtain an *indication* of the firms' financial positions and their probability of default, I have chosen to use two base models; Altman's z score and Emery and Cogger's Lambda. I shall reserve discussion of these two models for the subsequent section and will instead highlight the outcomes the two models produce and how I intend to use their results.

4.1) Altman's Z Score Model

As the name suggests, this model produces a firm specific z score which can be used to indicate the probability of default. I intend to apply two versions of the model to each of the firms in the data set, then to regress these results on the proportion of leasing used by each firm in T-2 (2010). Though the models produce a continuous set of outcomes, Altman suggests cut off points to interpret the scores, and subsequently offer credit terms to the company. Having a cut-off point will allow me to use a probit regression as well as a normal OLS regression to analyse the results as I will have two distinct predictions; "*default*" or "*safe*".

4.2) Emery and Cogger's Lambda

This model produces a liquidity index for the probability of technical insolvency. As with the Altman z model, I intend to use two versions with different values for the time variable, using both 4 and 6 year periods. I will discuss the implications of this in the next chapter. Unlike the Altman Z model, there is no cut-off point with which to interpret the results given by the index. Subsequently, I shall only employ a simple OLS regression to analyse the data, regressing the outcomes for this year (2012) on the proportion of leasing for the same data set in 2010.

5) The Credit Rating Models

5.1) Altman's Z Score

Altman's z score, developed by Edward I. Altman in 1968, is a solvency measure used by lending institutions, institutional investors, and occasionally, by companies requiring credit to establish the likelihood of future bankruptcy. The original model uses five differently weighted financial ratios to determine a z score which indicates the likelihood of default. By employing a 'Multivariate Discriminate Analysis' [MDA], Altman was able to build upon a previous credit rating model developed by William H. Beaver in 1966, whereby a 'univariate discriminate analysis' was used to predict business distress with accounting ratio's.

Using Multivariate Analysis, Altman was able to establish a stronger predictive model by incorporating several accounting ratio's into the Z score function, thereby forming a more holistic approach to evaluating the financial position of a firm.

The objective of Altman's Z score model is to classify firms into one of two *a priori* qualitative groups; bankrupt and non-bankrupt. The ratio's in Alman's Z make up the vector of variables that constitute a multivariate density function. "*The discriminant function maps the multidimensional characteristics of the density function of the populations variables into a one-dimensional measure, by forming a linear combination"* (Chung K. C., 2008). This takes the following form;

Equation 1

$$z_i = Xa + A0 + A1X1 + a2X2 + \cdots + anXn$$

Carrying out the MDA to arrive at the discriminant function required the following three steps;

1) Establishing explicit groups

2) Collecting relevant data for the objects in groups

3) Employing the MDA to establish the linear function which best discriminates between the two groups.

Altman's initial step was to select a sample of sixty six corporations split evenly into the two groups, bankrupt and non-bankrupt. All of the firms in his sample qualified as Small to Medium Sized [SME] businesses, with a profile of assets ranging from $0,7 to $25,9 million. Firms that possessed a value of assets that were outside of this range were considered small or very large, and were removed from the data set. This was due to the impracticality of obtaining data for very small companies, (something that incidentally has influenced the direction of this paper), and the fact that the incidence of bankruptcy in large firms is very rare.

Selecting the right profile of multiples to be included in the function essentially involved considering their individual significance in discerning bankrupt and non-bankrupt firms, as well as evaluating the inter-correlation between the variables. Ultimately, those variables that contributed to the highest predicting power of the firm when considered in unison were selected. Thus the contribution to the predictive power of the entire function was prioritised above the individual significance of the multiples.

The multiples that led to the best predictive power of the entire function were the following;

X1: Working Capital/Total Assets

X2: Retained Earnings/Total Assets

X3: Earnings before interest and taxes [EBIT]/Total Assets

X4: Market value of Equity/Book value of total debt

X5: Sales/Total Assets

Interpretation of Multiples

<u>X1: Working Capital/Total Assets</u>

The Working Capital/Total Assets ratio is a measure of the net liquid assets of the firm relative to its size, here given by the total value of assets. Altman defines working capital as the difference between current assets and current liabilities. He maintains that '*ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets'* (Altman, 1968). Thus, one would expect this to discriminate between the two groups quite effectively.

X2: Retained Earnings/Total Assets

This is a measure of cumulative profitability over time. Clearly, Retained earnings will amount over time, thus this measure implicitly accounts for the age of the firm. Consequently, the measure discriminates against younger firms whose reserves haven't had the chance to grow. As Altman points out, this is indicative of what happens in reality. Often younger firms will pose a less favourable credit rating simply because they have fewer liquid assets. The risk of short term insolvency therefore is relatively higher.

X3: EBIT/ Total Assets

This is a measure of the productivity if a firms assets, its ability to generate earnings from assets.

X4: Market Value of Equity/Book Value of Debt

The market value of equity is measured by the combined value of shares outstanding, both preferred and common. This ratio is significant because it adds a market based ratio to the function, making it slightly more forward looking than models strictly based on accounting ratios.

X5: Sales/Total Assets

Similar to X3, this ratio measures the ability of assets to generate sales. To that extent, it is also an efficiency measure of a firm's assets. By itself, this multiple is the least significant in discriminating between bankrupt and non-bankrupt firms. However, its relationship with the other variables in the function led to an overall contribution which strengthened its predictive power.

Significance of Multiples

To test the individual discriminating ability of the variables, Altman carried out an "F test". "*This relates the difference between the average values of the ratios in each group to the variability (or spread) of values of the ratios within each group*" (Altman, 1968). In other words, the F test looks to measure the extent to which differences in the mean of each multiple for both bankrupt and non-bankrupt firms can be explained by variation in the multiples themselves. The results for each of the five multiples are presented in table 1.

Table 1

Variable means and tests of significance			
Variable	Bankrupt Group mean n=33	Non Bankrupt group mean n=33	F Ratio
X1	-0.60%	41.40%	31.6
X2	-62.60%	35.50%	58.86
X3	-31.80%	15.30%	26.56
X4	40.10%	247.70%	33.26
X5	150%	190%	2.84

(Altman, 1968)

The level of significance is determined with cut-off points. An F ratio above 12 admits a significance level at 1% whilst an F ratio above 4 admits a significance level at 5%. Clearly, Multiples X1 to X4 are significant indictors of the differences in means between groups at the 1% level. X5 however, is not significant in explaining inter group mean variations and, as mentioned, is included solely due to its contribution to the function as a whole.

Calculating scaled vectors for each of the multiples gave an impression of the "contribution power" of each multiple, and leads to X3, X5 and X4 being classed as the biggest contributors respectively.

I have mentioned that the weights given to the individual multiples are dependent on the MDA assigning significance to each one. Altman's original model considers publicly held firms in the manufacturing sector and results in the weights being defined as follows;

Equation 2

$$z = 2.1X1 + 1.4X2 + 3.3X3 + 0.6X4 + \ 0.9X5$$

5.1.1) Accuracy of Original Model

The accuracy of the function is derived simply by calculating the proportion of firms that were correctly classified either as bankrupt or non-bankrupt (Hits) over the total number of firms in the sample. A “type 1” error in the results occurs when the function incorrectly predicts a bankrupt firm as non-bankrupt. A type 2 error occurs when the function incorrectly predicts a non-bankrupt firm as bankrupt.

Altman carried out the accuracy test for one year and two years prior to bankruptcy, using the same firms for both years. Applying the model to firms one year prior to bankruptcy or non-bankruptcy yielded 63 correct hits, representing 95% accuracy. Under these conditions, type 1 error stood at 6% whilst type 2 errors stood at 3%.

Using data two years prior to firm’s bankruptcy the results became less accurate, with type one error increasing to 28% and type 2 error increasing to 6%.

5.1.2) Application

Though the coefficients in the model were derived with a view to accurately predicting default among publicly traded firms in the manufacturing sector, Altman’s original model has been used to assess firms in a variety of business sectors. The appropriateness of this is a matter of some debate. For the purpose of the analysis carried out in this paper, I will use two variants of the model to gain a broader impression of the firms in my sample. After all, the purpose of my analysis is not to test the accuracy of the models employed, but to apply them with the assumption that the models are accurate. Using various forms of the models allows me to gain a broad impression of a firm's credit worthiness.

Interpreting the Z score requires a definition of bandwidths where one can determine the probability of bankruptcy with a minimum number of misclassifications. Altman concludes that, when applying the z score model with the coefficients defined in equation 1, all firms with a score less than 1.81 are bankrupt, whilst all those that yield a score higher than 2.99 fall into the non-bankrupt zone. The area between 1.81 and 2.99 is classified as the grey area due to the susceptibility to miscalculations.

For practical reasons, Altman established a critical value within the grey area that best discriminates between bankrupt and non-bankrupt firms. The value that discriminated between bankrupt and non-bankrupt firms with the least number of misclassifications was 2.675.

5.1.3) Variations of the Model

Although the original model is widely used for analysing different industry sectors, Altman's z score has been modified over time to tailor it for different types of industry. These new models differ in the weights they attribute to the different multiples used in the function. Through applying the same MDA methodology, a linear combination that best discriminates between the two groups (bankrupt and non-bankrupt) is derived.

In some cases, extra ratio's are included in the function to give weight to relevant industry-specific shortfalls in the model. This is a result of using scaled vectors to determine the individual contribution of different ratios to the discriminating power of the function as a whole. As the characteristics that define bankrupt and non-bankrupt firms will undoubtedly vary across industries, so the F statistics for the function's multiples will vary. For this reason, the contribution of different ratios to the discriminating power of the function will also vary across industries, necessitating slight variations in the multiples used in the Z score function, and the weights attributed to them.

As mentioned, I intend to apply two versions of the model, both developed by Altman himself. The first is the original model as described in equation 1. The second model is a revised version from Altman's 1977 paper *"Predicting the Financial Distress of Companies: revisiting the Z-score and Zeta models"*. In this paper, Altman developed several variations of the original Z score model for application to different industry sectors and for different types of company (for example private and public companies).

For the sake of my analysis, I have decided to apply the version of the model developed for non-manufacturing firms, although previous literature suggests that the original model works just as well when applied outside of the manufacturing sector. This model is specified in equation 2.

Equation 3

$$z = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4$$

The important difference with this version is that the fifth ratio, "Sales/Total Assets" has been eliminated. This minimizes "*the potential industry effect which is more likely to take place when such an industry sensitive variable as asset turnover is included*" (Alman, 1977). Interestingly, this model remains robust when there exists substantial variation in the types of asset financing employed by companies.

Numerous authors have taken the principle Multiple Discriminate Analysis technique and applied it to different industries using a variety of techniques to obtain a profile of coefficients. June Li, in her paper "*Prediction of Corporate Bankruptcy from 2008 Through 2011*" assesses the predictive power of several variants. Interestingly, she finds that including asset volatility into the model has little impact on the overall accuracy of the function. Perhaps her most relevant finding for the purpose of this analysis is that whilst the original Z score model was developed for manufacturing firms "*it performs equally well in predicting bankruptcy for non-manufacturing companies."* (Li, 2012)

Whilst I am aware that several version of the model may be more appropriate for certain companies in different industry sectors, I believe using the two models developed by Altman himself will be sufficient for this paper. Whether or not these models posit significant differences in accuracy will be something I discuss in more detail when analysing my results. However, the purpose of this paper is not to develop a model that accurately predicts corporate bankruptcy, but rather to assess the impact that leasing, as a proportion of a firms assets, has on a company's credit rating over time, as measured by the Altman Z models. For this reason, I will only be using those models previously mentioned as proxies for firm financial health.

5.1.4) Contemporary relevance of Altman's Original Model

Changes in the banking regulatory environment, notably Basel II and more recent developments in commercial banking have led financial institutions to adopt a lower risk profile. This has subsequently drawn light on credit rating systems as more companies struggle to establish new lines of credit in an increasingly austere economic environment. Due to its simplicity, Altman's Z score has been widely used in gaining a holistic view of a company's solvency. As such, it serves as an important decision tool for lenders, which in turn makes it useful for managers and CEO's in any leveraged company. Understanding how banks deduce credit ratings, and subsequently design the capital requirements incorporated into their loans is central to directing the management of a firm. Thus, the context of Altman's Z score is broad ranging. It serves a prominent role in lending organisations, and subsequently serves as an important decision metric for firms themselves.

To contextualise the latter point slightly - If a firm is facing the prospect of developing a new product line or in deed retiring an existing one, reducing its labour force or outsourcing a part of its operations, it could conceivably simulate the impact this will have on its credit rating. A company's operating decisions will all have a bearing on Altman's Z score and with enough information, it is relatively straightforward to anticipate the extent of this impact. Thus, the use of Altman's z score has a contemporary relevance as a managerial decision making tool, and is particularly appealing due to its simplicity.

5.2) Emery and Cogger´s Lambda

The second performance evaluation multiple I´ve chosen to use is Emery and Cogger´s Lambda. This is a liquidity index which is used as a proxy for predicting firm failure and has been derived from a probability distribution function describing the probability that the firm will become technically insolvent. Emery and Cogger define a firm as reaching technical insolvency when it is unable to meet short term cash requirements.

The Lambda index is argued to represent a marked improvement on Altman´s z score by offering a model that directly addresses issues pertaining to a firms cash flows. Though Altman´s Z score indirectly incorporates cash flows through looking at the net-working-capital-to-asset ratio, it is an inadequate measure of liquidity.

The lambda index therefore provides a radically different approach to assessing the financial position of a firm by concentrating on its liquidity position, rather than weighting different measures of firm success in one function.

The authors describe their approach as using an *"axiomatic description of a firm´s liquidity policy and liquidity position to obtain an expression for the likelihood that the firm will exhaust its liquid reserves (become technically insolvent)"* (Cogger, 1982, p. 290) That is to say, in forming their initial probability distribution function (pdf), Emery and Cogger use standard descriptors of, for example, the liquidity position, defined here as "*a firms provisions for meeting its obligations*" (Cogger, 1982, p. 291). From this they are able to form a broad pdf which describes the probability that a firm will reduce its liquid resources to the point of insolvency before, or at, time `T'.

5.2.1) Derivation of the Liquidity Index

As mentioned, the liquidity index that Emery and Cogger use as a proxy for predicting firm failure is derived from a pdf. This is itself formed with three basic assumptions underlying a stochastic process. These are;

(1) That there is a time horizon (T) over which a firm´s liquidity position is a matter of concern. The time horizon signifies the period over which it is costly to obtain extra liquid resources and may be unique to each firm. The liquid reserves held at the beginning of the period (L*o*) therefore constitute the stock of resources that are available to meet cash requirements during the time period.

(2) The firm's periodic net cash flows are independent, identically distributed, random variables. This is required for a stochastic method.

(3) During the time horizon, the liquid reserve balance is allowed to fluctuate randomly as long as it remains positive.

With these assumptions, the authors form their probability distribution function as follows;

Equation 4

$$F(T) = \emptyset = \left[\frac{-Lo - \mu T}{\sigma\sqrt{T}}\right] + exp\left[\frac{-2\mu Lo}{\sigma^2}\right]\emptyset\left[\frac{\mu T - Lo}{\sigma\sqrt{T}}\right]$$

Where

$\emptyset$ = The normal distribution function

μ, σ^2 = Mean and Variance of net cash flow per unit of time

Lo = Initial liquid reserve

T= Length of the period in units of time.

5.2.2) <u>Interpretation of the pdf</u>

The pdf as whole is quite intuitive. Concentrating on the first term, we can see that the probability of technical insolvency increases with the variability of cash flows over the period, but decreases if the initial liquid reserve and mean cash flow are relatively higher.

5.2.3) Using F(T) to Approximate Liquidity

There are two possible ways in which to use the pdf to approximate liquidity of a firm. One way is simply to apply it directly to a firm. The smaller the probability of technical insolvency as measured by the pdf, the more likely it is that the firm will be able to meet obligations and remain liquid throughout the period.

Alternatively, one can derive a statistic from the pdf which gives an indication of the *relative* liquidity across firms. The statistic is the negative of the first term in the pdf;

Equation 5

$$\lambda = \frac{Lo + \mu T}{\sigma\sqrt{T}}$$

Emery and Cogger argue that this is a reasonable method for measuring relative liquidity because, the first and second terms in the pdf measure *"the probability that the liquid reserve is exhausted on day T and prior to day T, respectively"* (Cogger, 1982, p. 293), and that these two probabilities tend to move together. As such, it should be possible to condense the two terms into the lambda statistic, and arrive at an index which exhibits most of the information contained in the pdf.

The authors provide an example, saying that a firm with high Lo and μ and a low σ^2 will likely have a high lambda index and a probability of insolvency on day 'T' close to zero. Conversely, a firm with low Lo and μ, and high σ^2 will have a relatively high probability of insolvency on day T. Thus the expression in equation … contains most of the information about relative liquidity, despite it being insufficient for calculating the probability of technical insolvency.

5.2.4) Empirical Evidence Supporting the Lambda Index for Predicting Failure

As I have mentioned, the Lambda index offers an improvement on Altman's Z score by way of incorporating issues firms may incur with cash flows, namely cash flow variability and uncertainty. Furthermore, Emery and Coggers liquidity index outperforms previous attempts at deriving a measure of liquidity which, by and large, have tended to adopt rather static approaches. The superiority of the lambda index over other liquidity models is due mainly to the fact that it is a dynamic measure of a firms' liquidity position. By altering firm specific cash flow variability through different time periods, the lambda index is capable of providing a detailed profile of a firms' liquidity position over time.

Through applying the Lambda liquidity index to a collection of fifty-two firms that filed for bankruptcy between 1949 and 1971, Emery and Cogger were also able to extend the application of the Lambda index as a failure predictor as well. In doing so, they expanded the definition of Lo to include all the resources that may be used to prevent ruin. This nicely foreshadows my application of the Lambda index, as I have chosen to include both '*cash and marketable securities'*, as well as *'unused lines of credit'* within the initial liquid reserve variable of the equation. With Lo defined as a "*total wealth position*", and with net cash flows measured as the periodic change in this variable, Emery and Cogger were able to apply the Lambda index to the data of fifty-two firms collected by Wilcox. Pairing similar firms in the data, Emery and Cogger calculated lambda index's for all the companies, and predicted those with the lowest lambda scores would fail. Comparing their results to those obtained by Wilcox, Emery and Cogger found that the overall accuracy of their model was superior to Wilcox's.

In a subsequent analysis, Emerry and Cogger also performed an unpaired classification test using lambda as a single discriminant variable. Again, this method yields more accurate results than those obtained using a multivariate analysis with the same accounting information.

5.2.5) Application

For the purpose of my analysis, I have taken the liberty of altering Emery and Cogger's method slightly, something I will cover in more detail in my methodology. Given the current nature of my data, however, I will not be able to test the accuracy of the revised model, perhaps a significant limitation to the approach I have used. I will however, assume that the accuracy of Emery and Cogger's broader model as described in the previous section is indicative of the way I have applied it.

5.2.6) Revised Model

To evaluate firms in my data set, I have had to take a retrospective approach to their accounting data, and develop a version of the lambda index which can be used to predict the probability that the firms will become technically insolvent. To do this, I have included several variables to arrive at a liquid reserve estimation. The function, as I have applied it, is described as follows;

Equation 6

$$\lambda' = \frac{(Cash\ \&\ MS) + Cred +/- [CFops - CFia]}{\sigma_{fcf}\sqrt{T}}$$

Where;

$Cash\ \&\ MS$ = Cash and Marketable Securities

$Cred$ = Unused lines of credit

$CFops$ = Cash flow from Operations

$CFia =$ Cash flow from investing activities

σ_{fcf} = Standard Deviation of free cash flow – Operation Cash Flow being used for two scenarios; T = 4 and T = 6

Most of the data necessary for calculating the revised lambda is available from the financial statements of the listed companies. The only variable that is harder to establish is the firm's unused lines of credit. Given that this is a key source of liquidity for most companies, any liquidity measure that excludes this information would doubtless be inaccurate.

Unfortunately, such information is rather difficult to obtain from the publicly available accounting information and I have therefore had to use a proxy to establish this. To do this, I looked at current liabilities as a proportion of total assets over a five year period prior to 2012. As a benchmark for the maximum level of credit lines, the maximum proportion of current liabilities over total assets for the five year period was chosen. The unused lines of credit were calculated as the residual between the maximum proportion of current liabilities over total assets, and the proportion of current liabilities that are presently being used.

By coincidence, the value of current liabilities over total assets was never larger than the five year historical maximum. However, in the instance where this had not been the case, I would have set the value for unused lines of credit at zero.

5.2.7) Points of Difference

The major difference between Emery and Cogger's model, and the one I have used, is the inclusion of Capital Expenditure. In Emery and Cogger's original Lambda, Operating Cash Flow is used in the numerator. The model I am using however subtracts capital expenditure from this to get a more accurate figure for free cash flow to the firm. Capital expenditure is a significant part of any companies financial statements and can sometimes be a significant contributor to pushing a firm towards bankruptcy. Often, managers with incentives to acquire businesses will invest in poorly performing companies, or at least, assets that will reduce the overall asset efficiency. As such, including capital expenditure in the lambda equation provides a more accurate view of a company's operations.

5.2.8) Calculating Lambda: deciding the value of "*T*"

My objective in analyzing firms lambda values is to regress company's proportion of leasing in 2010 (Y-2) and its probability of becoming technically insolvent in 2012 (Y), as measured by the revised lambda equation.

The data necessary for calculating the Lambda and Leasing variables for listed companies is available from Bloomberg. As such, there is no information I use which is not readily available to the public in company annual reports. As mentioned, I have used a slightly revised version of the Lambda equation to derive a probability of technical insolvency.

An important decision in applying this equation is deciding what to use as the unit of time over which the periodic net cash flows are defined. I have chosen to apply two alternatives to gain some impression of the impact this has on my regression results. These are, T=4 and T=6, representing four and six year periods prior to 2012 respectively.

Altering T in the lambda equation has two implications. Firstly, it changes the standard deviation of cash flows variable (σ_{fcf})since it changes the time horizon over which cash flows are considered. Secondly of course, it changes the $\sqrt{T}$ variable. Both of these variables occur in the denominator of the equation. Thus reducing the time horizon over which periodic cash flows occur would necessarily reduce the denominator, and would result in a probability of technical insolvency being relatively low.

6) Methodology

6.1) Public Companies

To summarise, my thesis aims to find support for the view that leasing, by way of granting increased access to financing, has more noticeable effects on smaller, younger firms, than it does larger, more established ones. I have in the previous section provided some intuition as to why smaller firms may prefer leasing over other forms of debt, and indicated that credit rating models could be used as a metric for success.

The subsequent pages will be devoted to describing the process through which my research will be conducted.

Regression Analysis

To establish the relation between leasing intensity and the model outputs, I intend to use regression analysis. Analysing the relationship between leasing and company credit ratings through regression analysis requires one to run several types of regressions to ensure that any correlation, or lack thereof, can be given a plausible explanation. In many cases, the true relationship between the variables is distorted by the fact that there exists a similarity between the two variables being compared. In other words, where an explaining variable is being regressed on a model output as an explained variable, and the model output incorporates similar variables to the explaining variable, some level of spurious correlation will arise.

Using the Altman Z score and Emery and Cogger's Lambda in regression analysis poses a significant threat of producing spurious correlations given the wide range of accounting data used in each model. In fact, there are few widely used performance measures that aren't already incorporated to some extent in each model. The following pages will detail the types of regressions I intend to run, and the ways I will try to control for spurious correlations.

6.1.2) Altman Z regressions

Regressions by Sector

1. **Altman Z on Leasing Intensity**

As previously mentioned, I will regress the intensity of both operational and capital leasing from 2010 on the original Altman Z outputs, as well as the revised 1977 model for 2012. In this case, I will use the model outputs as the explained (dependent) variables, and the intensity of leasing as the explaining (independent) variables.

To get a sense of the industry effect, I will conduct analysis on my data set where the firms are separated by sector, as well as a pooled data analysis.

2. **Altman Z on Firm Size**

Isolating firm size as an independent variable poses significant threat of producing spurious correlations given the fact that this is measured by asset value, a prominent variable in the Altman Z function. In order to control for spurious correlations occurring between firm size and the Altman Z outputs, I will rank the companies by size, then choose the top and bottom third, giving them a value of 1 and 0 respectively. These binomial values will be used as the independent variables and will ensure that I am discriminating between firms of significantly different asset sizes, without actually regressing the asset size on the Altman Z score.

3. **Reverse Correlations**

In order to establish a line of causation, I will perform reverse regressions on each sector, making the explained variables the intensity of leasing for each security with the model outputs on the x axis. In the case where both directions of regression are significant, the more significant regression will indicate the lines of causation. In other words, this will tell me whether variations in leasing intensity cause differences in credit ratings, or if credit rating variations cause differences in company leasing intensity.

4. Dummy Variables

I intend to run dummy regressions where I check for significance of simply using leasing or not. The results from the regression will tell me whether or not leasing, by itself, is enough to impact upon company credit ratings.

6.1.3) Pooled regressions

I will repeat each of the previous regressions on the pooled data set, ignoring the sectors that each firm is titled under. This will increase my sample size and give me an overall impression of the relationship between leasing and credit ratings.

5. Probit regressions

Although Altman's model produces a continuous set of Z scores, cut-off points, or bandwidths specific to each model make it possible to turn the continuous set of z scores into a dichotomous set of variables; "*default*" or "*safe*". As previously mentioned, Altman suggested that a z score of 2.675 is the best discriminator between bankrupt and non-bankrupt firms in the original model. For the revised 1977 model however, he does not carry out the same analysis and we are therefore left to decide upon an appropriate z score for discriminating between bankrupt and non-bankrupt firms.

When testing the revised models accuracy, Altman defined a grey area of 1.22 and 2.6. In other words, those firms whose z score's were bellow 1.22 would almost certainly go bankrupt, whilst those who's z scores were above 2.6 were almost guaranteed to remain solvent with a probability of 95%.

Although the original models "critical z score" is between the two boundaries of the grey area, I have chosen to use 2.6 as the discriminating z score. The consequence of this is that there is an increased likelihood of predicting default when interpreting the output of the model. Whether or not this is accurate for the individual firm is debatable. However, it is certainly indicative of what happens in reality as those firms whose Z scores fall bellow 2.6 will face significantly higher interest charges than those firms whose Z scores are above 2.6. In other words, a score bellow 2.6 is interpreted by financial institutions to represent decidedly more risk than a score above 2.6. The corresponding credit terms will therefore be significantly different.

6. Multiple Regression Analysis

Finally, to get a sense of how all relevant multiples effect the model outputs, I intend to run a multiple regression using; asset size, leasing intensity (as a proportion of assets) for both operational and capital leases and the nominal values of leasing for both operational and capital leases as the independent variables. Similar to the firm size regressions, I will control for spurious correlations by ordering the firms by asset set then assigning binomial values to the largest and smallest firms to regress on the model outputs.

6.1.4) Testing for Linearity & Heteroskedasticity

The OLS regressions used assume a linear relationship between the independent and dependent variables. This poses a risk of rendering relationships between the two insignificant when there exists a non-linear relationship.

In order to establish whether there are other types of relationships between the independent and dependent variables, I shall plot the residuals of the regressions on the pooled data set. In those cases where the residuals indicate a non-linear relationship, I shall test for Heteroskedasticity using Stata. This will indicate whether the pattern shown by the residual between the predicted and actual model outputs with varying levels of leasing intensity bears any statistical significance. Where heteroskedasticity is present, the null hypothesis, which in this case states that there is no relation between leasing intensity and a firms credit worthiness, must be rejected.

6.1.5) Lambda Regressions

The regression process for the lambda output is almost identical to that of the Altman Z regressions. After calculating the lambda's for each firm in my data set, I will regress the model outcomes on the intensity of capital and operational leasing from 2010 in the same way as I will for the Altman Z results. As mentioned however, this model does not provide a cut off point with which to interpret the results. Subsequently I will not be able to do a Probit regression on the pooled data.

As with the Altman Z data, I shall also be testing for heteroskedasticity to ensure that the OLS regressions are not invalidating significant relationships.

Summary of Regressions

For the sake of clarity, I have produced a table summarizing the regressions I will carry out. As well as specifying what variables are included in each regression, I have provided an index as to which figure or table the results appear in.

Table 2

Summary Of Regressions

Altman Z Model Regressions

No.	Pooled/Sector	Regression	Model	Independent Variable	Dependent Variable	Table
1	By Sector	OLS	Altman Z Model	Operating Leases as a proportion of Assets	Original Altman Z Model Output	12
2	By Sector	OLS	Altman Z Model	Capital Leases as a proportion of Assets	Original Altman Z Model Output	12
3	By Sector	OLS	Altman Z Model	Leasing being used as a Dummy variable	Original Altman Z Model Output	13
5	By Sector	OLS	Altman Z Model	Original Altman Z Model Output	Operating Leases as a proportion of Assets	14
6	By Sector	OLS	Altman Z Model	Original Altman Z Model Output	Capital Leases as a proportion of Assets	14
7	Pooled	OLS	Altman Z Model	Operating Leases as a proportion of Assets	Original Altman Z Model Output	15
8	Pooled	OLS	Altman Z Model	Capital Leases as a proportion of Assets	Original Altman Z Model Output	15
9	Pooled	OLS	Altman Z Model	Leasing being used as a Dummy variable	Original Altman Z Model Output	28
10	Pooled	OLS	Altman Z Model	Firm Size	Original Altman Z Model Output	29
11	Pooled	OLS	Altman Z Model	Original Altman Z Model Output	Operating Leases as a proportion of Assets	30
12	Pooled	OLS	Altman Z Model	Original Altman Z Model Output	Capital Leases as a proportion of Assets	30
13	Pooled	Probit	Altman Z Model	Operating Leases as a proportion of Assets	Original Altman Z Model Output	32-35
14	Pooled	Probit	Altman Z Model	Capital Leases as a proportion of Assets	Original Altman Z Model Output	32-35
15	Pooled	Multiple OLS	Altman Z Model	Asset size, Capital and Operational lease values as a proportion of assets, Nominal Values of Capital and Operational Leases	Original Altman Z Model Output	31

Table 3

Emerry and Cogger's Lambda Regressions

No.	Pooled/Sector	Regression	Model	Independent Variable	Dependent Variable	Figure
31	Sector	OLS	Lambda index	Operating Leases as a proportion of Assets	Lambda index T=4 model output	36
32	Sector	OLS	Lambda index	Capital Leases as a proportion of Assets	Lambda index T=4 model output	36
33	Sector	OLS	Lambda index	Leasing being used as a Dummy variable	Lambda index T=4 model output	37
35	Sector	OLS	Lambda index	Lambda index model output	Operating Leases as a proportion of Assets	38
36	Sector	OLS	Lambda index	Lambda index model output	Capital Leases as a proportion of Assets	38
37	Pooled	OLS	Lambda index	Operating Leases as a proportion of Assets	Lambda index T=4 model output	39
38	Pooled	OLS	Lambda index	Capital Leases as a proportion of Assets	Lambda index T=4 model output	39
39	Pooled	OLS	Lambda index	Leasing being used as a Dummy variable	Lambda index T=4 model output	50
40	Pooled	OLS	Lambda index	Firm Size	Lambda index T=4 model output	49
41	Pooled	OLS	Lambda index	Lambda index T=4 model output	Operating Leases as a proportion of Assets	48
42	Pooled	OLS	Lambda index	Lambda index T=4 model output	Capital Leases as a proportion of Assets	48
43	Pooled	Multiple OLS	Lambda index	Asset size, Capital and Operational lease values as a proportion of assets, Nominal Values of Capital and Operational Leases	Lambda index T=4 model output	51

6.2) Private Companies

The methodology employed for private sector companies will be very similar to that used for large companies. The main difference between samples is that I will only be regressing the Altman Z score on leasing intensities for private companies as I have insufficient data for calculating the Lambda index. Additionally, I will only be carrying out pooled regressions on the private sector companies as there are not enough companies within each category (Micro, Small and Medium), to do categorised regressions.

The regressions I will carry out on the private sector companies are summarised in table 4 bellow.

Table 4

		Variables		
	Type	**Independent**	**Dependent**	**Table**
1	**Normal Regressions**	Leasing / Assets	Altman Z score	
2	**Dummy regressions**	Leasing / Assets	Altman Z score	
3	**Reverse Regressions**	Altman Z score	Leasing / Assets	

6.2.1) Altman Z Model for Private Companies

The model I have chosen to use for the private sector companies in Portugal is described in figure 2.

Equation 7

$$Z = 0{,}717X1 + 0{,}847X2 + 3.107X3 + 0{,}420X4 + 0{,}998X5$$

Where;

X1 = Working Capital / Total Assets

X2 = Retained Earnings / Total Assets

X3 = EBIT / Total Assets

X4 = Book value of Equity / Total liabilities

X5 = Sales / Total Assets

The main difference between this model and the original and revised models I use for the public sector companies is that X4 uses the book value of equity rather than the market value of equity.

7) Data

7.1 Data from Bloomberg

The data for public companies has been obtained entirely from Bloomberg. Due to the fact that much of the literature I have used to form my hypothesis is based on analysis of European companies, I have chosen to use data for companies listed in the FTSE All World European Index.

The average asset size of the firms across the six sectors I have analysed, before removing securities from the data set, is € 27.206.165.116,55. Table 4 provides descriptive statistics of the firms by sector.

Table 5

	Average AssetSsize	Standard Deviation
Consumer Discretionary	21.479.691.850,98 €	46.177.583.091,25 €
Consumer Staples	20.240.666.471,69 €	21.328.061.166,88 €
Energy	48.892.171.702,68 €	77.252.612.143,40 €
Industrials	15.145.009.241,78 €	18.254.293.948,35 €
Materials	17.090.544.854,73 €	22.707.672.731,47 €
Utilities	40.388.906.577,43 €	56.515.631.168,53 €

The values for asset size have been taken from 2012 data and serve only to provide an impression of the size of firms being considered. When calculating the Altman Z and Lambda probabilities, the original currencies were used, whilst the values in table 4 have been converted into Euro's.

The number of observations I will use for each regression are presented in tables 5 and 6. These figures vary according to which model output I am using in the regression as they required different types of information. In those cases where firms didn't have enough data registered on Bloomberg to calculate either the lambda or Z score I discounted the firm from the data set.

Table 6

Number of observations by sector for Altman Z	
Consumer Discretionary	46
Consumer Staples	39
Energy	41
Industrials	57
Materials	41
Utilities	37

Table 7

Number of observations by sector for Lambda	
Consumer Discretionary	75
Consumer Staples	39
Energy	29
Industrials	98
Materials	65
Utilities	29

7.2) Data for small companies

Data for small companies was obtained from www.portaldaempresas.pt. All the companies that have been used in the sample have been classed into one of three groups; Micro, Small and Medium sized. These represent classes for the asset sizes of the companies, the descriptive statistics for which as presented in tables 7 to 9.

Table 8

Asset Size Statistics For Sample (€)	
Max	181.171.325,20
Min	7.313,57
St dev	32.551.831,15
Mean	10.804.476,96
Nr of Observations	69

Table 9 – Sample Description According to Firm Size

Size Desciption	Frequency	Mean Asset size
Micro	32	9.774.630,74~~2~~
Small	20	11.384.825,49
Medium	17	11.789.833,02
Total	69	

Table 10 – Sample Description according to Leasing Usage

Leasing Activity	Frequency	% of Sample
Use Leasing	17	24,64%
Don't Use Leasing	52	75,36%
Total	69	

7.3) Limitations

1. The most significant limitation in conducting this research has been in calculating the unused lines of credit for the lambda index. Although I have been able to arrive at a proxy for this variable, it undoubtedly contains a high degree of inaccuracy.

2. Another prominent limitation is the number of observations used for some sectors. The lowest number of observations I have used is in running regressions for securities within the utilities sector. The deficiency of observations is due to the fact that, in many cases, there simply isn't enough information on individual securities on Bloomberg. By conducting pooled regressions I will of course increase the number of observations and perhaps gain more accurate regression results, though this will get rid of any sector specific trends.

3. Due to the cost involved in obtaining data from for private sector companies from www.portaldaempresas.com, I have only had access to data from 2011. Though accounting data for one year is sufficient to calculate the Altman Z scores, it is not enough to calculate the Emery and Cogger index due to its inclusion of cash flow volatility over a period of 'T' years, where T is greater than 1.

4. Another consequence of the limited data for private sector companies has been that I am unable to perform regressions using the intensity of operational leasing as there are not enough firms in the data set that use it. Instead, I will concentrate on using capital leasing intensities in the regressions for private sectors.

8) Results

8.1) Public Sector Results

My regressions have all been summarised into tables in the appendix. In each case, I have chosen to include the variables used, the R squared statistic, the Significance of F, the Coeffiecients and the P values. To preserve space, I have abbreviated the variables to the following form; *'Independent Variable/Dependent Variable'*. If for example I conduct a regression where I am using Operational Leasing intensity as the independent variable and the Altman Z score as the dependent variable, I shall use the following form 'Op/ALZ'.

Table 11 provides an index of the abbreviations I have used for each regression.

Table 11

Variable	Abreviation
Operating Leasing Intensity	Op
Capital Leasing Intensity	Cap
Asset size	Size
Original Altman Z output	ALZ
Revised Altman Z Output	ALZ 77
Lambda Output (T=4)	T=4
Lambda Output (T=6)	T=6

The tables of results from my regressions can be found in tables 12 to 52 in the appendix.

Heteroskedasticity Test

After plotting the residuals for the *pooled* data regressions, there seemed to be some evidence of heteroskedasticity as the errors clearly don't follow a constant pattern. In other words, there was not a constant variation in the error terms for each observation. What is in fact observed is higher errors at lower levels of leasing intensity compared to higher levels of leasing intensity. These plots are presented in figures 2 to 5 in the appendix for the Altman Z regressions, and 6 to 9 for the Lambda regressions. To establish whether this variance in errors is a significant consequence of differences in leasing intensity, I have conducted a Breush-pagan test and White's test's for Heteroskedasticity and homoskedasticity. The results from these tests are presented in tables 16 to 23 for the pooled Altman Z regressions and 40 to 47 for the pooled Lambda regressions.

8.1.1) Altman Z Regressions

Sectoral OLS Regressions (Tables 12 to 14)

This set of regressions includes the standard Altman Z output regressions on Leasing intensity, the dummy variables and the reverse regressions. The overriding impression from the summary statistics of the OLS regressions is that leasing intensity has little bearing on a firm's credit worthiness over time. As a firm's Altman's Z score is influenced by a plethora of managerial decisions as well as external factors such as the economic environment in which the firm operates, it is easy to understand why leasing intensity has such little relevance for a firms credit rating, for larger firms at least. Nonetheless, if one accepts that leasing is but a small part of the managerial toolset deployed by managers to finance their assets, it is interesting to find that there are some instances where the correlation between leasing and a firm's z score is almost significant.

An example of this can be seen when regressing Operational Leases from 2010 on the 1977 Z scores in the Consumer Staples sector. The results from this regression posit an F statistic of only 6.5% and an R squared of 8,8% making it the most significant in the sectoral regressions. These results are shown in table 12 of the appendix. The fact that the most significant observation is found within the consumer staples industry may indicate some sort of industry specific structure that is more sensitive to differences in leasing intensities. Whether or not that is true however certainly cannot be ascertained from these results as it is still statistically insignificant.

<u>Pooled Regressions</u> (Tables 15 to 35)

If there was any indication of a relation between leasing and credit ratings at a sector level, the regressions conducted on the pooled data certainly doesn't support this. The only conclusion that can be drawn from the results at a pooled level is that variations in leasing intensity bear absolutely no impact on the credit rating of large, listed firms. The same can be said for the multiple and probit regression results where again the R squared, and pseudo R squared statistics are incredibly small.

The results for each of the pooled regressions are presented in the appendix in the following tables;

Pooled Regressions	
Regression	Table
OLS	15
Dummy	28
Firm Size	29
Reverse	30
Multiple	31
Probit	32 to 35

<u>Heteroskedasticity Test's</u> (Tables 16 to 23)

The Breusch-Pagan Test for Heteroskedasticity shows that when regressing the Altman Z model outputs on leasing intensity in the normal OLS regressions, there is significant Heteroskedasticity as the p values are substantially bellow 0,05. The results for these tests are presented in tables 16 to 23 of the appendix.

To control for the problem of Heteroskedasticity, I have run Generalized Least Squares regressions on the pooled Altman Z data. This test indicates whether the error terms in each observation are affected by the independent variables. The results for this test are presented in figures 24 to 27.

The results from the Generalized Least Squares regressions indicate that, after controlling for heteroskedasticity, there is still no relation between the error terms of the regressions and the leasing intensities of firms. By comparison, the results from the Generalized Least Squared regressions are very similar to those of the Ordinary Least

Squared regressions. In fact, the only difference is that the confidence intervals have narrowed which, given that the r squared statistics are so small, is not relevant.

8.1.2) Lambda Regressions

Sectoral OLS Regressions (Tables 36 to 38)

The results from the OLS show a weak effect of the proportion of leasing on a company's credit rating over time. In some cases, the significance of F exceeds 90%, rendering any sign of correlation completely unreliable. Despite this however, there are some points of interest that one should bear in mind when looking at the results from the OLS regression.

Firstly, within the sectoral regressions, the highest significance found is within the Materials sector where the probability of technical insolvency using T=6 is regressed on Capital leasing in 2010. This produces an R squared of approximately 17% with an F statistic of 0.04%. The results are presented in table 36 of the appendix.

Although there is little sign of correlation between leasing intensity in Y-2 and a firms solvency ratio in 2012, it is interesting to note that the most reliable results come from the Materials sector, and might admit something of the relative advantage of using a higher proportion of leasing in this sector compared to others. Again however, I would be hesitant in relying on this data to support this conclusion and would use it instead only as a guide towards further investigation.

Pooled Data (Tables 39 to 51)

As with the Altman Z regressions, the pooled data proves even less significant than the sectoral data on all counts. The highest significance occurs when regressing the Lambda output with T=6 on capital leasing intensity where the R squared equals 0,7% and the F statistic equals 10%.

The firm size, reverse, dummy and multiple regressions also lack any indication of significance and are generally less significant than the sectoral regressions. The tables these regressions appear in are summarized in the following table;

Pooled Regressions	
Regression	**Table**
OLS	39
Dummy	50
Firm Size	49
Reverse	48
Multiple	51

Heteroskedasticity Test's (Tables 40 to 47)

The Breush Pagan tests for the lambda regressions indicate that heteroskedasticity isn't present as the P value is greater than 5%. For this reason, I have not conducted Breush-Pagan and White's tests on the lambda data.

8.2) Private Sector Results

(Tables 52 to 54)

Contrary to what I have suggested in my hypothesis, the regressions performed on private sector companies indicate that there is little relation between leasing intensity and company credit ratings. In fact, the results from these regressions are for the most part much less significant than those of the public companies with F statistics ranging from 92% to 97% and the highest R squared statistic being 0.13%.

Although the results point towards there being very little relationship between leasing intensity and company credit ratings, I would be interested to find out if the results hold when the same analysis is applied to a larger sample size. Given the limited data I have had, I would be hesitant to conclude that the results from these regressions are in deed indicative of the impact leasing can have on SME's in Portugal. What can be taken from the results however is that when considering the impact leasing has on company credit ratings, the distinction between large and small firms is not as clear as the literature reviewed in this paper would suggest.

Conclusion

The evidence from the regressions I have carried out indicate quite clearly that variations in leasing intensity have a negligible effect on companies' credit ratings both for small and large companies. I have in my hypothesis suggested that the reason for this is that leasing is but one of the many managerial tools employed to improve credit ratings among management. One other plausible explanation is that larger corporations, relative to small companies, are less sensitive to changes in cash flow. This is certainly supported by much of the literature reviewed prior to this analysis.

However, whilst these explanations could conceivably be true for larger corporations, they don't go very far in explaining the lack of significance found among small companies. Firstly, small companies generally have a more limited selection of financing tools call upon relative to large companies, and secondly, it has been shown that small companies are in-deed much more sensitive to variations in cash flow than large organizations. One would think therefore that those sources of financing that allow companies to invest in assets whilst keeping their cash flow positive would give the users of those financing sources a relative advantage. This is certainly not supported by the results in this study however.

What I am left to conclude therefore is that given the results obtained, there is little reason to believe that leasing can have any tangible impact upon a firms credit position. Unfortunately, speculating upon the explanations for the lack of significance found among smaller companies is outside of the scope of this paper and I can therefore only offer a suggestion as to how this line of research might be continued.

Given the data limitations I have highlighted, I would suggest conducting more detailed analysis into private company data to gain a clearer view of their leasing behavior. This would afford a more informed line of research on the effect leasing has on credit ratings, or any other success metric. That being said, it is still entirely possible that this research would pose similar results to those I have obtained here, thereby reinforcing my conclusion that variations in leasing intensity have a remarkably small impact on firm credit ratings.

Appendix

PUBLIC COMPANY REGRESSION RESULTS

Regressions: Independent Variable = Leasing Intensities - Dependent Variable = Original and Revised Altman z Probabilities

Table 12

					Coefficients		P value's	
Sector	**Resgression**	**Variables**	**R squared**	**Significance of F**	**Intercept**	**Slope (X variable 1)**	**Intercept**	**Slope (X variable 1)**
Consumer Staples	1	Op/ALZ	0,017114307	0,427299963	2,890766	0,835916493	3,24925E-17	0,427299963
Observations = 39	2	Cap/ALZ	0,000105959	0,950408432	2,976942	-0,653102444	8,86203E-19	0,950408432
	3	Op/ALZ 77	0,088813134	0,065376739	4,137561	-3,753328846	1,7368E-13	0,065376739
	4	Cap/ ALZ 77	0,070705107	0,10180804	3,977788	-33,25309937	5,20326E-14	0,10180804
Energy	5	Op/ALZ	0,007977373	0,626881998	2,674207	1,68411004	3,87789E-12	0,626881998
Observations = 32	6	Cap/ALZ	0,016194937	0,487634434	2,833509	-11,20058855	6,92788E-14	0,487634434
	7	Op/ALZ 77	0,002212856	0,798214676	3,769955	1,665256923	2,86047E-09	0,798214676
	8	Cap/ ALZ 77	0,006080879	0,671406811	3,940826	-12,88541787	1,16282E-10	0,671406811
Utilities	9	Op/ALZ	0,014229596	0,515514605	1,675374	18,82030952	0,009964671	0,515514605
Observations = 32	10	Cap/ALZ	0,007008055	0,648736131	2,089125	-21,44221661	0,000191635	0,648736131
	11	Op/ALZ 77	0,004169926	0,725494942	2,607533	18,1670246	0,023364493	0,725494942
	12	Cap/ ALZ 77	0,020130044	0,438578776	3,254508	-64,80111424	0,000781989	0,438578776
Consumer Discretionary	13	Op/ALZ	0,014039297	0,432879288	2,378337	0,641841696	6,33857E-15	0,432879288
Observations = 46	14	Cap/ALZ	0,003204381	0,708655051	2,426529	5,289228691	2,80164E-15	0,708655051
	15	Op/ALZ 77	0,035527491	0,209666845	6,833364	2,939251022	4,67874E-15	0,209666845
	16	Cap/ALZ 77	0,013294716	0,445433776	7,000853	31,01408393	2,18848E-15	0,445433776
Industrials	17	Op/ALZ	0,035169243	0,162438671	14,67007	-35,01755931	0,000160579	0,162438671
Observations = 57	18	Cap/ALZ	0,044487268	0,455582871	12,6455	-72,38932429	0,000262662	0,455582871
	19	Op/ALZ 77	0,027848269	0,214712724	22,73417	-44,17949529	4,80404E-05	0,214712724
	20	Cap/ ALZ 77	0,009778736	0,464265916	20,29823	-100,6769503	4,74675E-05	0,464265916
Materials	21	Op/ALZ	0,013397358	0,471125071	3,077085	-3,667996198	7,40881E-27	0,471125071
Observations = 41	22	Cap/ALZ	1,62798E-06	0,993683031	3,014684	-0,107050954	3,73443E-30	0,993683031
	23	Op/ALZ 77	0,016637582	0,42154588	8,841142	-10,78684139	2,93964E-28	0,42154588
	24	Cap/ ALZ 77	0,011660234	0,501575844	8,748834	-23,90835338	8,22523E-32	0,501575844

Regressions: Leasing Usage = Dummy Independent Variable

Table 13

					Coefficients		P values	
Sector	**Resgression**	**Variables**	**R squared**	**Significance of F**	**Intercept**	**Slope (X variable 1)**	**Intercept**	**Slope (X variable 1)**
Consumer Staples	1	Op/ALZ	4,48721E-05	0,967716426	3,014613821	-0,042870792	0,006200784	0,967716426
Observations = 39	2	Cap/ALZ	0,078144332	0,084799022	3,454399635	-0,647611616	3,60534E-13	0,084799022
	3	Op/ALZ 77	0,003199881	0,732317526	3,072611975	0,746125682	0,158893902	0,732317526
	4	Cap/ ALZ 77	0,146484675	0,016182942	5,158443177	-1,827401414	6,59694E-10	0,016182942
Energy	5	Op/ALZ	0,008437954	0,485561944	3,019766852	-0,330917243	5,93913E-08	0,485561944
Observations = 32	6	Cap/ALZ	0,00328954	0,755196711	2,630289659	0,148439302	8,30729E-07	0,755196711
	7	Op/ALZ 77	0,036214156	0,296836054	4,597076476	-0,924665396	2,08706E-06	0,296836054
	8	Cap/ ALZ 77	0,005636833	0,682987475	3,549380257	0,364806874	0,000109113	0,682987475
Utilities	9	Op/ALZ	0,009920146	0,587572121	1,365839935	0,6890442	0,37252162	0,61706476
Observations = 32	10	Cap/ALZ	0,04786003	0,228996579	2,7689125	-1,113264543	0,001123267	0,228996579
	11	Op/ALZ 77	0,008437954	0,61706476	1,899203941	1,133171943	0,37252162	0,61706476
	12	Cap/ ALZ 77	0,06390981	0,162722362	4,539509319	-2,293954682	0,002248145	0,162722361
Consumer Discretionary	1	Op/ALZ	0,014616013	0,298197168	3,067060421	-0,430414739	5,42749E-12	0,298197168
Observations = 46	2	Cap/ALZ	0,067637406	0,023276046	3,179958548	-0,728497678	4,36493E-20	0,023276046
	3	Op/ALZ 77	0,032378183	0,119850263	10,1552076	-2,514462012	1,07003E-09	0,119850263
	4	Cap/ ALZ 77	0,048087905	0,057004688	9,625317157	-2,411008841	1,16687E-14	0,057004688
Industrials	5	Op/ALZ	0,00227961	0,633695078	7,979033213	2,434915933	0,089283619	0,633695078
Observations = 57	6	Cap/ALZ	0,006228767	0,430412529	8,140656725	3,072294454	0,008358872	0,430412529
	7	Op/ALZ 77	0,005108401	0,475313727	12,23601775	5,005718283	0,057867192	0,475313727
	8	Cap/ ALZ 77	0,006486768	0,420991483	13,79024505	4,3057237	0,001259596	0,420991483
Materials	9	Op/ALZ	0,003678051	0,620583138	2,947228656	0,08305252	1,15601E-29	0,620583138
Observations = 41	10	Cap/ALZ	0,003219273	0,643314463	3,059102639	-0,067051409	1,9724E-36	0,643314463
	11	Op/ALZ 77	0,005908618	0,530151531	8,367128554	0,299978926	1,34628E-29	0,530151531
	12	Cap/ ALZ 77	0,000344388	0,879700796	8,648812365	-0,06249664	3,48782E-36	0,879700796

Reverse Regressions

Table 14

					Coefficients		P values	
Sector	Resgression	Variables	R squared	Significance of F	Intercept	Slope (X variable 1)	Intercept	Slope (X variable 1)
Consumer Staples	1	ALZ on Op	2,15211E-06	0,99255079	0,088561939	0,000154497	0,131642383	0,99255079
	2	ALZ on CAP	0,003641002	0,700703096	0,007709496	-0,000633351	0,185660471	0,700703096
	3	ALZ 77 on op	0,078522606	0,068754789	0,162551481	-0,018761225	0,000932769	0,068754789
	4	ALZ 77 on CAP	0,058982516	0,116594516	0,012042542	-0,001620585	0,012131872	0,116594516
Energy	5	ALZ on Op	0,008465993	0,56721844	0,046370435	-0,003574006	0,028972187	0,56721844
Observations = 32	6	ALZ on CAP	0,039447001	0,213183619	0,01061558	-0,001603581	0,015276998	0,213183619
	7	ALZ 77 on op	0,006102776	0,627330531	0,042005276	-0,001523386	0,010001479	0,627330531
	8	ALZ 77 on CAP	0,017057317	0,415699772	0,008003011	-0,000529382	0,01690391	0,415699772
Utilities	9	ALZ on Op	0,021547329	0,385967794	0,01161033	0,00099326	0,000985948	0,385967794
Observations = 32	10	ALZ on CAP	0,003427002	0,730724406	0,005294007	-0,000232899	0,00905673	0,730724406
	11	ALZ 77 on op	0,007384427	0,613064028	0,012572714	0,000326673	0,000196588	0,613064028
	12	ALZ 77 on CAP	0,014750622	0,473950796	0,005610692	-0,000271459	0,003174957	0,473950796
Consumer Discretionary	13	ALZ/ Op	0,014039297	0,432879288	0,085648534	0,021873457	0,260959566	0,432879288
	14	ALZ/ Cap	0,003204381	0,708655051	2,426529189	5,289228691	2,80164E-15	0,708655051
	15	ALZ 77/op	0,035527491	0,209666845	0,052073912	0,01208726	0,494490219	0,209666845
	16	ALZ77/Cap	0,013294716	0,445433776	0,004727455	0,000428667	0,291980133	0,445433776
Industrial	17	ALZ/ Op	0,035169243	0,162438671	0,095765826	-0,001004332	1,80635E-06	0,162438671
	18	ALZ/ Cap	0,010162633	0,455582871	0,014306125	-0,000140389	0,003719974	0,455582871
	19	ALZ 77/op	0,027848269	0,214712724	0,09597741	-0,000630344	3,42855E-06	0,214712724
	20	ALZ77/Cap	0,009778736	0,464265916	0,014507266	-9,71298E-05	0,004346984	0,464265916
Materials	21	ALZ/ Op	0,013397358	0,471125071	0,028134877	-0,003652501	0,073728652	0,471125071
	22	ALZ/ Cap	1,62798E-06	0,993683031	0,003911414	-1,52075E-05	0,505623105	0,993683031
	23	ALZ 77/op	0,013397358	0,471125071	0,028134877	-0,003652501	0,073728652	0,471125071
	24	ALZ77/Cap	0,011660234	0,501575844	0,008087355	-0,000487705	0,205886126	0,501575844

Pooled Regressions

Normal Linear Regressions

Table 15

				Coefficients		P value's	
Resgression	Variables	R squared	Significance of F	Intercept	Slope (X variable 1)	Intercept	Slope (X variable 1)
1	Op/ALZ	0,001254977	0,600405083	4,203558792	-2,057679994	1,66787E-10	0,600405083
2	Cap/ALZ	0,000904168	0,656623975	4,150334562	-14,42840673	4,39697E-11	0,656623975
3	Op/ALZ77	0,0001818	0,842015162	7,744544726	-1,286373553	1,40188E-12	0,842015162
4	Cap/ALZ77	0,000475719	0,747116965	7,769751713	-17,19012242	1,28094E-13	0,747116965

Figure 3

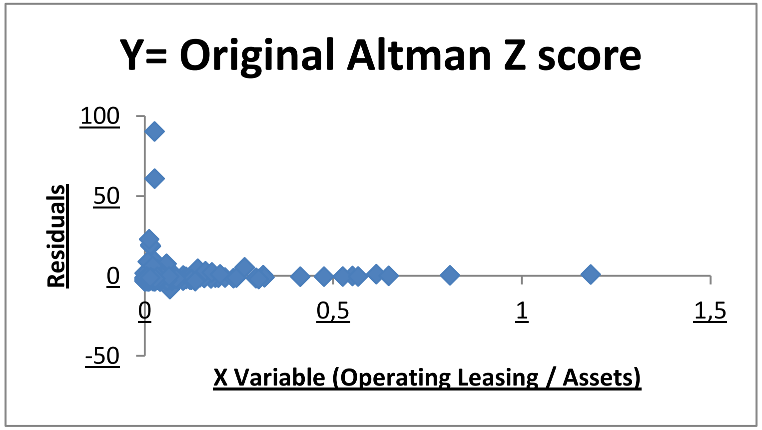


Figure 2

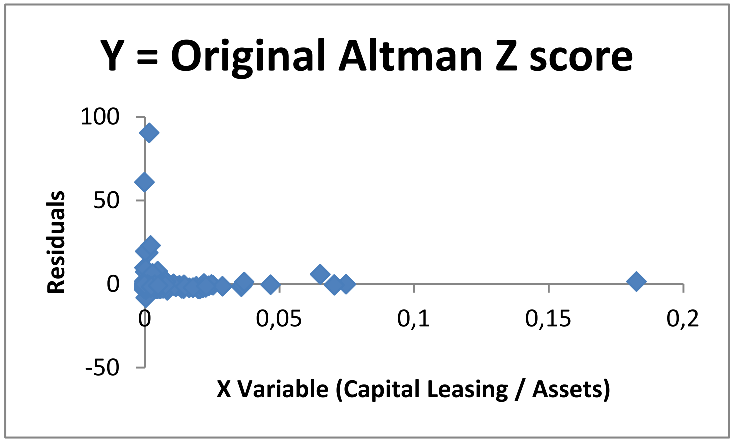


Figure 5

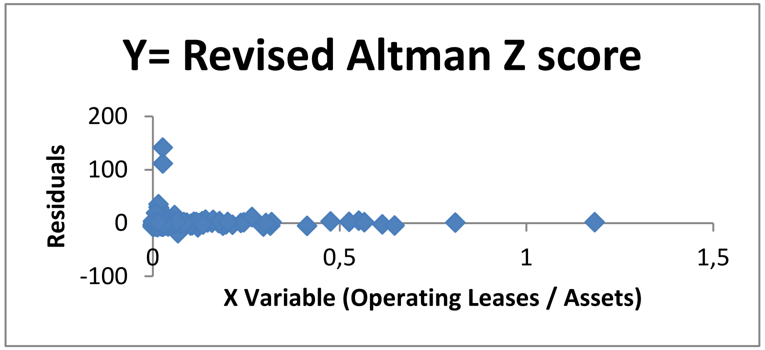
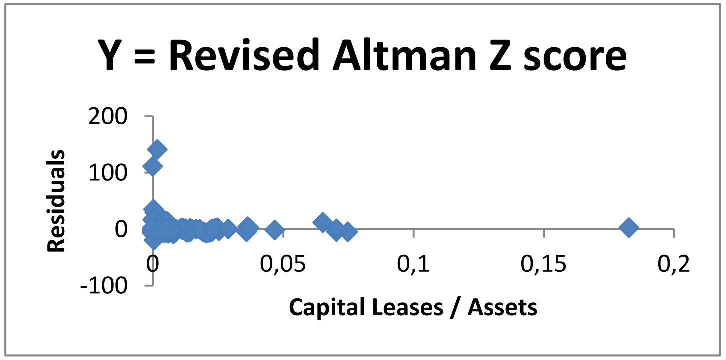


Figure 4



Testing For Heteroskedasticity

Pooled Altman Z data analysis: Checking for the significance of Heteroskedasticity with single regressions

1) **Dependent**: ALZ
   Indepdendent: Operating Leases / Assets

Breush-Pagan Test

Table 16

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of ALZ__12_

         chi2(1)      =    13.36
         Prob > chi2  =   0.0003
```

White's Test

Table 17

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(2)      =      0.47
         Prob > chi2  =    0.7894

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	0.47	2	0.7894
Skewness	1.99	1	0.1585
Kurtosis	1.46	1	0.2262
Total	3.93	4	0.4160

2) **Dependent:** ALZ
Independent: Capital Leases / Assets

Breush-Pagan Test

Table 18

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of ALZ__12_

         chi2(1)      =    11.38
         Prob > chi2  =   0.0007
```

White's Test Table 19

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(2)      =     0.52
         Prob > chi2  =   0.7705

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	0.52	2	0.7705
Skewness	1.97	1	0.1605
Kurtosis	1.46	1	0.2262
Total	3.96	4	0.4121

3) Dependent: ALZ 77
Independent: Operational Leases / Assets

Hettest

Table 20

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of ALZ_1993__12_

         chi2(1)      =    11.87
         Prob > chi2  =   0.0006
```

White's Test

Table 21

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(2)      =     0.44
         Prob > chi2  =   0.8030

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	0.44	2	0.8030
Skewness	2.24	1	0.1347
Kurtosis	1.76	1	0.1842
Total	4.44	4	0.3497

4) Dependent: ALZ 77
Independent: Capital Leases / Assets

Breusch-Pagan Test

Table 22

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of ALZ_1993__12_

         chi2(1)      =    10.52
         Prob > chi2  =   0.0012
```

White's Test

Table 23

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(2)      =      0.52
         Prob > chi2  =    0.7693

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	0.52	2	0.7693
Skewness	2.23	1	0.1354
Kurtosis	1.76	1	0.1842
Total	4.52	4	0.3405

General Least Squared Regressions

Dependent: AlZ – Independent: Operating leases / Assets

Table 24

```
. regress ALZ__12_ op_Assets__10_

      Source |       SS       df       MS              Number of obs =     221
-------------+------------------------------           F(  1,   219) =    0.28
       Model |  18.4755981     1  18.4755981           Prob > F      =  0.6004
    Residual |  14703.3915   219  67.1387741           R-squared     =  0.0013
-------------+------------------------------           Adj R-squared = -0.0033
       Total |  14721.8671   220  66.9175778           Root MSE      =  8.1938

------------------------------------------------------------------------------
     ALZ__12_ |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
op_Asset~10_ |   -2.05768   3.922521    -0.52   0.600    -9.788402    5.673042
       _cons |   4.203559   .6267369     6.71   0.000     2.968351    5.438767
------------------------------------------------------------------------------

. glm ALZ__12_ op_Assets__10_

Iteration 0:   log likelihood = -777.42803

Generalized linear models                          No. of obs      =       221
Optimization     : ML                              Residual df     =       219
                                                   Scale parameter =  67.13877
Deviance         =  14703.39152                    (1/df) Deviance =  67.13877
Pearson          =  14703.39152                    (1/df) Pearson  =  67.13877

Variance function: V(u) = 1                        [Gaussian]
Link function    : g(u) = u                        [Identity]

                                                   AIC             =  7.053647
Log likelihood   = -777.4280348                    BIC             =  13521.19

------------------------------------------------------------------------------
             |                 OIM
    ALZ__12_ |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
op_Asset~10_ |   -2.05768   3.922521    -0.52   0.600     -9.74568     5.63032
       _cons |   4.203559   .6267369     6.71   0.000     2.975177    5.431941
------------------------------------------------------------------------------
```

Dependent: AlZ – Independent: Capital Leases / Assets

Table 25

```
. regress ALZ__12_ Cap_Assets__10_

      Source |       SS       df       MS              Number of obs =     221
-------------+------------------------------           F(  1,   219) =    0.20
       Model |   13.311036     1   13.311036           Prob > F      =  0.6566
    Residual |  14708.5561   219  67.1623565           R-squared     =  0.0009
-------------+------------------------------           Adj R-squared = -0.0037
       Total |  14721.8671   220  66.9175778           Root MSE      =  8.1953

------------------------------------------------------------------------------
    ALZ__12_ |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Cap_Asse~10_ |  -14.42841   32.40973    -0.45   0.657     -78.3033    49.44648
       _cons |   4.150335   .5980961     6.94   0.000     2.971574    5.329095
------------------------------------------------------------------------------

. glm ALZ__12_ Cap_Assets__10_

Iteration 0:   log likelihood = -777.46684

Generalized linear models                          No. of obs      =       221
Optimization     : ML                              Residual df     =       219
                                                   Scale parameter =  67.16236
Deviance         =  14708.55608                    (1/df) Deviance =  67.16236
Pearson          =  14708.55608                    (1/df) Pearson  =  67.16236

Variance function: V(u) = 1                        [Gaussian]
Link function    : g(u) = u                        [Identity]

                                                   AIC             =  7.053999
Log likelihood   = -777.4668411                    BIC             =  13526.36

------------------------------------------------------------------------------
             |                 OIM
    ALZ__12_ |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Cap_Asse~10_ |  -14.42841   32.40973    -0.45   0.656    -77.95031     49.0935
       _cons |   4.150335   .5980961     6.94   0.000     2.978088    5.322581
------------------------------------------------------------------------------
```

Dependent: ALZ 77 – Independent: Operating Leases / Assets

Table 26

```
. regress ALZ_1993__12_ op_Assets__10_

      Source |       SS       df       MS              Number of obs =     221
-------------+------------------------------           F(  1,   219) =    0.04
       Model |  7.22066243     1  7.22066243           Prob > F      =  0.8420
    Residual |  39710.3385   219  181.325747           R-squared     =  0.0002
-------------+------------------------------           Adj R-squared = -0.0044
       Total |  39717.5592   220   180.53436           Root MSE      =  13.466

------------------------------------------------------------------------------
ALZ_1993~12_ |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
op_Asset~10_ |  -1.286374   6.446267    -0.20   0.842    -13.99103    11.41829
       _cons |   7.744545   1.029979     7.52   0.000     5.714605    9.774484
------------------------------------------------------------------------------

. glm ALZ_1993__12_ op_Assets__10_

Iteration 0:   log likelihood = -887.21347

Generalized linear models                          No. of obs      =       221
Optimization     : ML                              Residual df     =       219
                                                   Scale parameter =  181.3257
Deviance         =   39710.3385                    (1/df) Deviance =  181.3257
Pearson          =   39710.3385                    (1/df) Pearson  =  181.3257

Variance function: V(u) = 1                        [Gaussian]
Link function    : g(u) = u                        [Identity]

                                                   AIC             =  8.047181
Log likelihood   = -887.2134741                    BIC             =  38528.14

------------------------------------------------------------------------------
             |                 OIM
ALZ_1993~12_ |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
op_Asset~10_ |  -1.286374   6.446267    -0.20   0.842    -13.92083    11.34808
       _cons |   7.744545   1.029979     7.52   0.000     5.725823    9.763266
------------------------------------------------------------------------------
```

Dependent: ALZ 77 – Independent: Capital Leases / Assets

Table 27

```
. regress ALZ_1993__12_ Cap_Assets__10_

      Source |       SS       df       MS              Number of obs =     221
-------------+------------------------------           F(  1,   219) =    0.10
       Model |  18.8943973     1  18.8943973           Prob > F      =  0.7471
    Residual |  39698.6648   219  181.272442           R-squared     =  0.0005
-------------+------------------------------           Adj R-squared = -0.0041
       Total |  39717.5592   220   180.53436           Root MSE      =  13.464

------------------------------------------------------------------------------
ALZ_1993~12_ |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Cap_Asse~10_ |  -17.19012   53.24494    -0.32   0.747    -122.1282    87.74795
       _cons |   7.769752   .9825935     7.91   0.000     5.833202    9.706301
------------------------------------------------------------------------------

. glm ALZ_1993__12_ Cap_Assets__10_

Iteration 0:   log likelihood = -887.18099

Generalized linear models                          No. of obs      =       221
Optimization     : ML                              Residual df     =       219
                                                   Scale parameter =  181.2724
Deviance         =  39698.66476                    (1/df) Deviance =  181.2724
Pearson          =  39698.66476                    (1/df) Pearson  =  181.2724

Variance function: V(u) = 1                        [Gaussian]
Link function    : g(u) = u                        [Identity]

                                                   AIC             =  8.046887
Log likelihood   = -887.1809854                    BIC             =  38516.47

------------------------------------------------------------------------------
             |                 OIM
ALZ_1993~12_ |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Cap_Asse~10_ |  -17.19012   53.24494    -0.32   0.747    -121.5483    87.16804
       _cons |   7.769752   .9825935     7.91   0.000     5.843904      9.6956
------------------------------------------------------------------------------
```

Pooled Dummy's

Table 28

				Coefficients		P value's	
Resgression	Variables	R squared	Significance of F	Intercept	Slope (X variable 1)	Intercept	Slope (X variable 1)
1	Op/ALZ	0,002029248	0,505273628	2,358196085	1,76890268	0,363580135	0,505273628
2	Cap/ALZ	0,004495424	0,321098202	3,517927462	4,324456369	0,408608852	0,321098202
3	Op/ALZ77	0,000841643	0,667977653	4,59290576	-0,648561143	0,001070774	0,667977653
4	Cap/ALZ77	4,09313E-05	0,92465551	7,844424646	-0,234922493	0,000681547	0,92465551

Pooled Firm Size

Table 29

				Coefficients		P values	
Resgression	Variables	R squared	Significance of F	Intercept	Slope (X variable 1)	Intercept	Slope (X variable 1)
1	Size/ ALZ	0,0001629	0,877236187	3,94827081	0,165827689	5,78048E-07	0,877236187
2	Size/ ALZ 77	0,0104187	0,215458601	8,53165223	-2,29304399	8,24506E-10	0,215458601

Pooled Reverse

Table 30

				Coefficients		P values	
Resgression	Variables	R squared	Significance of F	Intercept	Slope (X variable 1)	Intercept	Slope (X variable 1)
1	ALZ/op	0,001255	0,600405083	0,07852525	-0,000609899	2,65204E-12	0,600405083
2	ALZ/Cap	0,0009042	0,656623975	0,00741148	-6,26658E-05	2,55579E-08	0,656623975
3	ALZ 77/Op	0,0001818	0,842015162	0,07713765	-0,000141328	2,20952E-11	0,842015162
4	ALZ 77/Cap	0,0004757	0,747116965	0,00736948	-2,7674E-05	7,40489E-08	0,747116965

Multiple Regression Analysis

Table 31

$$Alt\ Z = f\ (Asset\ size, Leasing\ Intensity, Value\ of\ Leasing)$$

Regression Statistics	
R Square	0,002257305
Adjusted R Square	-0,032628804
Observations	149

ANOVA	df	SS	MS	F	Significance F
Regression	5	14,19635956	2,839271911	0,064704969	0,99711404
Residual	143	6274,87946	43,88027594		
Total	148	6289,075819			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	4,149898603	0,862219372	4,81304264	3,73576E-06	2,445556324	5,854240882	2,445556324	5,854240882
asset size	0,049919659	1,22214793	0,04084584	0,967475768	-2,36589058	2,465729898	-2,36589058	2,465729898
op/assets	-1,986278153	4,467342743	-0,444621841	0,657265264	-10,81683956	6,844283252	-10,81683956	6,844283252
cap/assets	-1,601501541	33,15875453	-0,048298	0,961546138	-67,14615188	63,9431488	-67,14615188	63,9431488
op/assets x assets	2,58942E-11	1,3896E-10	0,186342657	0,852440145	-2,48787E-10	3,00575E-10	-2,48787E-10	3,00575E-10
cap/assets x assets	-1,00128E-10	6,39326E-10	-0,156614704	0,875769407	-1,36388E-09	1,16362E-09	-1,36388E-09	1,16362E-09

$$Alt\ Z\ 77 = f\ (Asset\ size, Leasing\ Intensity, Value\ of\ Leasing)$$

Regression Statistics	
Multiple R	0,111993135
R Square	0,012542462
Adjusted R Square	-0,021984025
Observations	149

ANOVA	df	SS	MS	F	Significance F
Regression	5	235,7759459	47,15518918	0,36327073	0,872955099
Residual	143	18562,44253	129,8072904		
Total	148	18798,21848			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	8,869833567	1,48297095	5,981124289	1,69208E-08	5,938456507	11,80121063	5,938456507	11,80121063
asset size	-2,469270223	2,102028711	-1,174708133	0,242063922	-6,624333911	1,685793464	-6,624333911	1,685793464
op/assets	-3,814686582	7,683589262	-0,496471955	0,620323778	-19,00277729	11,37340412	-19,00277729	11,37340412
cap/assets	2,993941364	57,0312745	0,052496484	0,958206361	-109,7393322	115,7272149	-109,7393322	115,7272149
op/assets x assets	3,16172E-11	2,39004E-10	0,132287409	0,894942922	-4,40819E-10	5,04054E-10	-4,40819E-10	5,04054E-10
cap/assets x assets	-1,37671E-10	1,09961E-09	-0,125200465	0,900540688	-2,31125E-09	2,03591E-09	-2,31125E-09	2,03591E-09

Probit regressions

1) **Dependent:** Original ALZ_
Independent: Operating Leases / Assets

Table 32

```
. probit Probit__12_ op_Assets__10_

Iteration 0:   log likelihood = -153.07465
Iteration 1:   log likelihood =  -147.7368
Iteration 2:   log likelihood = -147.69729
Iteration 3:   log likelihood = -147.69727
Iteration 4:   log likelihood = -147.69727

Probit regression                                 Number of obs   =        221
                                                  LR chi2(1)      =      10.75
                                                  Prob > chi2     =     0.0010
Log likelihood = -147.69727                       Pseudo R2       =     0.0351
```

Probit__12_	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
op_Asset~10_	2.59878	.9473339	2.74	0.006	.7420397	4.45552
_cons	-.1349078	.1022917	-1.32	0.187	-.3353958	.0655802

2) **Dependent:** Original ALZ
Independent: Capital Leases / Assets

Table 33

```
. probit Probit__12_ Cap_Assets__10_

Iteration 0:   log likelihood = -153.07465
Iteration 1:   log likelihood = -152.16786
Iteration 2:   log likelihood = -152.16584
Iteration 3:   log likelihood = -152.16584

Probit regression                                 Number of obs   =        221
                                                  LR chi2(1)      =       1.82
                                                  Prob > chi2     =     0.1776
Log likelihood = -152.16584                       Pseudo R2       =     0.0059
```

Probit__12_	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Cap_Asse~10_	7.536936	6.034586	1.25	0.212	-4.290635	19.36451
_cons	-.011764	.0931772	-0.13	0.900	-.1943879	.1708599

3) <u>Dependent:</u> ALZ 77

<u>Independent:</u> Operating Leases / Assets

Table 34

```
. probit Probit__12_0 op_Assets__10_

Iteration 0:   log likelihood = -115.65686
Iteration 1:   log likelihood = -115.46871
Iteration 2:   log likelihood = -115.46823
Iteration 3:   log likelihood = -115.46823

Probit regression                                 Number of obs   =        221
                                                  LR chi2(1)      =       0.38
                                                  Prob > chi2     =     0.5391
Log likelihood = -115.46823                       Pseudo R2       =     0.0016

------------------------------------------------------------------------------
Probit__12_0 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
op_Asset~10_ |     .43909   .7333021     0.60   0.549    -.9981556    1.876336
       _cons |   .7498086   .1077538     6.96   0.000     .5386151    .9610021
------------------------------------------------------------------------------
```

4) **<u>Dependent</u>: ALZ 77**

<u>Independent</u>: Capital Leases / Assets

Table 35

```
. probit Probit__12_0 Cap_Assets__10_

Iteration 0:   log likelihood = -115.65686
Iteration 1:   log likelihood = -115.29681
Iteration 2:   log likelihood = -115.29185
Iteration 3:   log likelihood = -115.29185

Probit regression                                 Number of obs   =        221
                                                  LR chi2(1)      =       0.73
                                                  Prob > chi2     =     0.3929
Log likelihood = -115.29185                       Pseudo R2       =     0.0032

------------------------------------------------------------------------------
Probit__12_0 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Cap_Asse~10_ |  -4.479096   5.098382    -0.88   0.380    -14.47174    5.513549
       _cons |   .8161542   .1027964     7.94   0.000     .6146771    1.017631
------------------------------------------------------------------------------
```

Emery and Cogger's Lambda Regressions

Stage 1: Regressions: Leasing intensities regressed on Lambda scores for T=4 and T=6

Table 36

					Coefficients		P Values	
Sector	**Resgression**	**Variables**	**R squared**	**Significance of F**	**Intercept**	**Slope (X variable 1)**	**Intercept**	**Slope (X variable 1)**
Consumer Staples	1	Op/T=4	0,0312576	0,281618014	0,029911	0,220522652	0,346673878	0,281618014
Observations = 39	2	Cap/T=4	0,0077351	0,594443168	0,054429	-0,881574142	0,065927532	0,594443168
	3	Op/T=6	0,032112	0,275031774	0,039973	0,220473958	0,204366533	0,275031774
	4	Cap/T=6	0,0002109	0,930071232	0,059628	-0,14360068	0,042912993	0,930071232
Energy	5	Op/T=4	0,0851662	0,124514884	0,146071	-1,040785922	0,002021478	0,124514884
Observations = 32	6	Cap/T=4	0,0004752	0,910628472	0,104369	-0,419544198	0,013942841	0,910628472
	7	Op/T=6	0,1062273	0,084450184	0,161657	-1,138478897	0,000567195	0,084450184
	8	Cap/T=6	0,0002551	0,934459528	0,115166	-0,301071238	0,00630344	0,934459528
Utilities	9	Op/T=4	0,0016105	0,836251161	0,049245	0,301387143	0,129683608	0,836251161
Observations = 32	10	Cap/T=4	0,0285968	0,38051589	0,065831	-1,776484744	0,015414216	0,38051589
	11	Op/T=6	0,0012336	0,856466709	0,062101	0,300588332	0,095169206	0,856466709
	12	Cap/T=6	0,0370052	0,317436214	0,082194	-2,302961209	0,00835214	0,317436214
Consumer Discretionary	1	T=4/Op	0,0013424	0,754986481	0,034478	0,011778474	0,000692211	0,754986481
	2	T=4/Cap	0,0011008	0,080446735	0,037167	-0,227794673	0,000116377	0,777495785
	3	T=6/Op	0,0010623	0,781318206	0,042491	-0,010030737	2,00369E-05	0,781318206
	4	T=6/Cap	0,0044923	0,567766347	0,043232	-0,440523759	4,48898E-06	0,567766347
	8	T=6/Cap	0,005626	0,421544533	0,162114	-2,417041819	2,67744E-20	0,421544533
Industrials	9	T=4/Op	0,0507544	0,02572275	0,026736	0,145515387	0,001643907	0,02572275
	10	T=4/Cap	0,0731498	0,007071009	0,031326	0,499657916	3,32878E-05	0,007071009
	11	T=6/Op	0,0691313	0,008905679	0,039573	0,217032071	0,000263757	0,008905679
	12	T=6/Cap	0,0588093	0,01613192	0,04823	0,572536968	1,09338E-06	0,01613192
Materials	13	T=4/Op	0,0027383	0,678885132	0,064772	-0,339681366	0,000437083	0,678885132
	14	T=4/Cap	0,2262674	6,21392E-05	0,031938	9,653994476	0,017585743	6,21392E-05
	15	T=6/Op	7,231E-05	0,94640145	0,07318	0,057552325	0,00015951	0,94640145
	16	T=6/Cap	0,1769681	0,000484475	0,048235	8,902030346	0,001088532	0,000484475

Stage 2 regressions: Leasing as dummy variables regressed on Lambda scores

Table 37

					Coefficients		P Values	
Sector	**Resgression**	**Variables**	**R squared**	**Significance of F**	**Intercept**	**Slope (X variable 1)**	**Intercept**	**Slope (X variable 1)**
Consumer Staples	1	Op/T=4	1,92145E-16	1	5,827512929	0	1,09951E-07	#NUM!
Observations = 39	2	Cap/T=4	-1,30554E-16	1	3,883620949	0	1,47246E-08	#NUM!
	3	Op/T=6	0,009626093	0,552368349	5,063213648	1,146448921	0,002503158	0,552368349
	4	Cap/T=6	0,004755257	0,676582701	4,209468187	-0,488770856	7,95369E-05	0,676582701
Energy	5	Op/T=4	1,92145E-16	1	5,827512929	0	1,09951E-07	#NUM!
Observations = 32	6	Cap/T=4	0,050180846	0,242729689	4,219741937	-1,292157719	9,32886E-05	0,242729689
	7	Op/T=6	0,009626093	0,552368349	5,063213648	1,146448921	0,002503158	0,552368349
	8	Cap/T=6	0,116976318	0,069367799	3,708197386	-1,622528882	2,46114E-05	0,069367799
Utilities	9	Op/T=4	0,032740787	0,347557424	1,513735183	3,990010092	0,709944098	0,347557424
Observations = 32	10	Cap/T=4	0,035686221	0,326382566	1,25775388	2,848592996	0,651036044	0,326382566
	11	Op/T=6	0,015745936	0,516601607	4,092575082	1,568757876	0,05397811	0,516601607
	12	Cap/T=6	0,005542387	0,7011201	3,449007705	0,636459523	0,0201073	0,7011201
Consumer Discretionary	1	T=4/Op	0,000878404	0,800719579	0,031498431	0,005541386	0,117558604	0,800719579
	2	T=4/Cap	0,00030428	0,88191656	0,034433223	0,00257201	0,014877703	0,88191656
	3	T=6/Op	0,008610414	0,428466672	0,054857276	-0,016608417	0,00503194	0,428466672
	4	T=6/Cap	0,003520938	0,613072439	0,035767335	0,008375494	0,008355559	0,613072439
Industrials	9	T=4/Op	0,000127277	0,912208083	0,034616636	0,002275915	0,072475694	0,912208083
	10	T=4/Cap	0,000841507	0,776757597	0,033938052	0,004224231	0,0046861	0,776757597
	11	T=6/Op	0,003062965	0,588325796	0,042005596	0,014268112	0,087387916	0,588325796
	12	T=6/Cap	0,001770769	0,68076958	0,04936104	0,007830948	0,001370827	0,68076958
Materials	13	T=4/Op	0,01135887	0,398112353	0,038027901	0,027324644	0,190354026	0,398112353
	14	T=4/Cap	0,040518886	0,107858649	0,028922911	0,044726797	0,209582028	0,107858649
	15	T=6/Op	0,020244788	0,258207732	0,043578978	0,038035496	0,148837178	0,258207732
	16	T=6/Cap	0,02661049	0,194159627	0,047843013	0,037792968	0,050183475	0,194159627

Stage 4 regressions: Reverse regressions

Table 38

					Coefficients		P Values	
Sector	Resgression	Variables	R squared	Significance of F	Intercept	Slope (X variable 1)	Intercept	Slope (X variable 1)
Consumer Staples	1	T=4 on OP	0,031257613	0,281618014	0,07796514	0,141743322	0,001089978	0,281618014
Observations = 39	2	T=4 on Cap	0,032112034	0,275031774	0,076310227	0,145650011	0,001624533	0,275031774
	3	T=4 on Cap	0,007735124	0,594443168	0,007010842	-0,008774218	0,015797221	0,594443168
	4	T=4 on Cap	0,000210944	0,930071232	0,006670404	-0,00146896	0,024190173	0,930071232
Energy	5	T=4 on OP	0,085166197	0,124514884	0,050651864	-0,081828736	5,04715E-05	0,124514884
Observations = 32	6	T=4 on Cap	0,000475241	0,910628472	0,005658004	-0,001132756	0,009897151	0,910628472
	7	T=6 on op	0,106227318	0,084450184	0,052891741	-0,093306357	3,89039E-05	0,084450184
	8	T=6 on cap	0,000255117	0,934459528	0,005638586	-0,000847363	0,01268155	0,934459528
Utilities	9	T=4 on OP	0,001610531	0,836251161	0,015335929	0,005343728	6,17333E-05	0,836251161
Observations = 32	10	T=4 on Cap	0,028596833	0,38051589	0,007554338	-0,016097427	0,002658526	0,38051589
	11	T=6 on op	0,001233556	0,856466709	0,015350121	0,004103806	7,49981E-05	0,856466709
	12	T=6 on cap	0,037005241	0,317436214	0,007759153	-0,016068547	0,002342715	0,317436214
Consumer Discretionary	13	T=4 on OP	0,001342353	0,754986481	0,131836569	0,113966649	2,00501E-05	0,754986481
	14	T=4 on Cap	0,001100797	0,777495785	0,004950941	-0,004832409	0,000477009	0,777495785
	15	T=4 on Cap	0,001062342	0,781318206	0,140304183	-0,105908711	1,40424E-05	0,781318206
	16	T=4 on Cap	0,004492301	0,567766347	0,005195996	-0,010197637	0,000429442	0,567766347
Industrials	21	T=4 on OP	0,050754416	0,02572275	0,054805043	0,348790719	2,07845E-05	0,02572275
	22	T=4 on Cap	0,073149848	0,007071009	0,005136205	0,146399858	0,227464805	0,007071009
	23	T=6 on op	0,069131299	0,008905679	0,050283797	0,318530337	0,000122584	0,008905679
	24	T=6 on cap	0,058809276	0,01613192	0,004918773	0,102716993	0,267974202	0,01613192
Materials	25	T=4 on OP	0,002738288	0,678885132	0,01486346	-0,008061343	1,74646E-08	0,678885132
	26	T=4 on Cap	0,226267406	6,21392E-05	0,001491473	0,023437698	0,024774437	6,21392E-05
	27	T=6 on op	7,23053E-05	0,94640145	0,014287707	0,001256341	1,55322E-07	0,94640145
	28	T=6 on cap	0,176968117	0,000484475	0,00142387	0,019879523	0,046880091	0,000484475

Pooled regressions

Normal Linear Regressions

Table 39

All Sectors	Resgression	Variables	R squared	Significance of F	Coefficients: Intercept	Coefficients: Slope (X variable 1)	P Values: Intercept	P Values: Slope (X variable 1)
	1	Op/T=4	0,000737491	0,620925642	0,04780397	0,021724963	5,50354E-12	0,620925642
	2	Cap/T=4	0,005243173	0,186798667	0,04703323	0,349260879	3,48206E-13	0,186798667
	3	Op/T=6	0,000321191	0,744173776	0,06058745	0,015034095	2,37291E-16	0,744173776
	4	Cap/T=6	0,007736465	0,10859048	0,0587463	0,444876001	1,32622E-17	0,10859048

Residual Plots

Figure 6

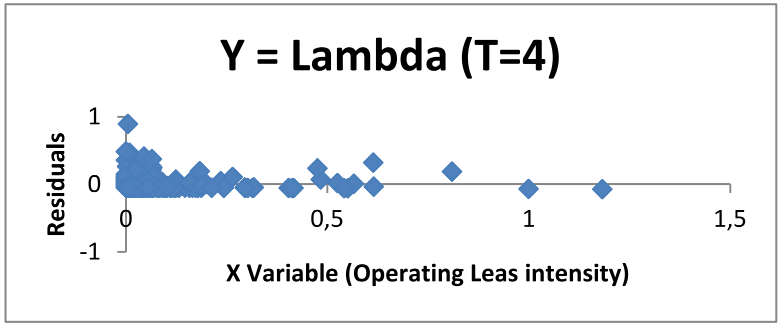


Figure 7

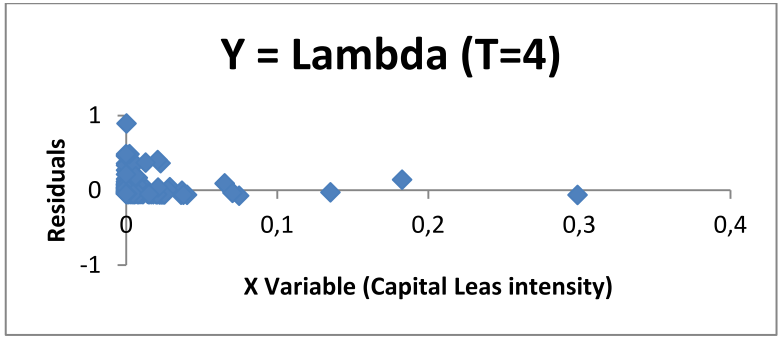


Figure 8

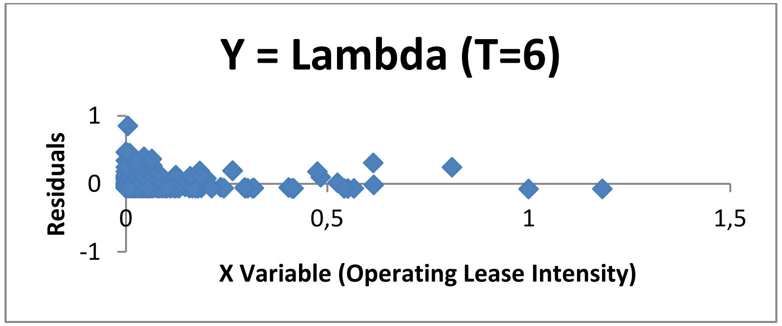
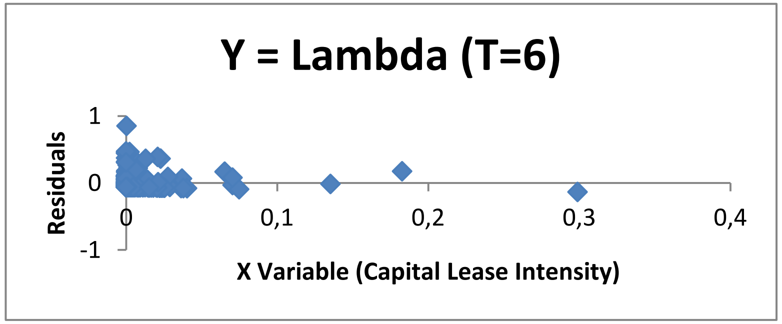


Figure 9



Testing for Heteroskedasticity with pooled lambda data

1) Dependent: Lambda probability (T=4) = **E**
Independent: Operating Leases / Assets = **H**

Hettest

Table 40

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of E

         chi2(1)      =     0.22
         Prob > chi2  =   0.6356
```

White's Test

Table 41

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(2)      =     0.14
         Prob > chi2  =   0.9309

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	0.14	2	0.9309
Skewness	12.14	1	0.0005
Kurtosis	6.42	1	0.0113
Total	18.71	4	0.0009

2) Dependent: Lambda Probability (T=4) = E

Independent: Capital Leases / Assets = I

Breusch-Pagan Test

Table 42

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of E

         chi2(1)      =     2.87
         Prob > chi2  =   0.0903
```

White's Test

Table 43

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(2)      =     1.54
         Prob > chi2  =   0.4628

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	1.54	2	0.4628
Skewness	12.26	1	0.0005
Kurtosis	6.81	1	0.0091
Total	20.60	4	0.0004

3) Dependent: Lambda Probability (T=6) = G

Independent: Operational Leases / Assets = H

Breusch-Pagan Test

Table 44

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of G

         chi2(1)      =     0.97
         Prob > chi2  =   0.3248
```

White's Test

Table 45

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(2)      =     0.35
         Prob > chi2  =   0.8403

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	0.35	2	0.8403
Skewness	15.10	1	0.0001
Kurtosis	5.79	1	0.0161
Total	21.24	4	0.0003

4) Dependent: Lambda Probability (T=6) = G
Independent: Capital Leases / Assets = I

Breusch-Pagan Test

Table 46

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of G

         chi2(1)      =    11.20
         Prob > chi2  =   0.0008
```

White’s Test

Table 47

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(2)      =     5.01
         Prob > chi2  =   0.0819

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	5.01	2	0.0819
Skewness	14.44	1	0.0001
Kurtosis	5.68	1	0.0171
Total	25.13	4	0.0000

Pooled Reverse

Table 48

					Coefficients		P Values	
All Sectors	Resgression	Variables	R squared	Significance of F	Intercept	Slope (X variable 1)	Intercept	Slope (X variable 1)
	1	T=4/Op	0,0007375	0,186798667	0,066327	0,033946703	1,18273E-14	0,620925642
	2	T=4/Cap	0,0052432	0,186798667	0,005697	0,015012196	3,49488E-05	0,186798667
	3	T=6/Op	0,0003212	0,744173776	0,066684	0,021364176	5,79211E-14	0,744173776
	4	T=6/Cap	0,0077365	0,10859048	0,005365	0,01739016	0,000157898	0,10859048

Pooled Firm Size

Table 49

					Coefficients		P Values	
All Sectors	Resgression	Variables	R squared	Significance of F	Intercept	Slope (X variable 1)	Intercept	Slope (X variable 1)
	1	Size/T=4	0,004076503	0,342591641	0,050109511	-0,013727152	1,86094E-06	0,342591641
	2	Size/T=6	0,005294575	0,279286295	0,066928673	-0,016748207	4,31149E-09	0,279286295

Pooled Dummy's

Table 50

					Coefficients		P Values	
All Sectors	Resgression	Variables	R squared	Significance of F	Intercept	Slope (X variable 1)	Intercept	Slope (X variable 1)
	1	Op/T=4	0,0003367	0,738289572	0,054164	-0,005702609	0,00067399	0,738289572
	2	Cap/T=4	0,0001873	0,80323736	0,047195	0,003153074	6,34086E-06	0,80323736
	3	Op/T=6	0,0003839	0,721258293	0,067077	-0,006385272	6,28479E-05	0,721258293
	4	Cap/T=6	0,000668	0,637894216	0,057478	0,006244717	1,81429E-07	0,637894216

Multiple Regression Analysis

Table 51

$$Lambda\ (T = 4) = f\ (Asset\ size, Leasing\ Intensity, Value\ of\ Leasing)$$

Regression Statistics	
R Square	0,025955471
Adjusted R Square	0,003512049
Standard Error	0,107550921
Observations	223

ANOVA	df	SS	MS	F	Significance F
Regression	5	0,066886445	0,013377289	1,156484559	0,331726241
Residual	217	2,510082534	0,011567201		
Total	222	2,576968979			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0,042883648	0,011615049	3,692076435	0,000281427	0,019990895	0,065776402	0,019990895	0,065776402
Asset Size	-0,009553037	0,016408638	-0,582195587	0,561039333	-0,041893745	0,022787672	-0,041893745	0,022787672
Op/Assets	0,030367995	0,06407464	0,473947177	0,636014087	-0,095920318	0,156656308	-0,095920318	0,156656308
Cap/Assets	0,860455835	0,575350733	1,495532699	0,136228346	-0,273535289	1,99444696	-0,273535289	1,99444696
Op/Assets x Assets	-1,62476E-12	4,32794E-12	-0,375411438	0,707721193	-1,01549E-11	6,90542E-12	-1,01549E-11	6,90542E-12
Cap/Assets x Assets	-6,70115E-13	2,49165E-11	-0,026894476	0,978568616	-4,97794E-11	4,84391E-11	-4,97794E-11	4,84E-11

$$Lambda\ (T = 6) = f\ (Asset\ size, Leasing\ Intensity, Value\ of\ Leasing)$$

Regression Statistics	
R Square	0,040296976
Adjusted R Square	0,018184003
Standard Error	0,114290305
Observations	223

ANOVA	df	SS	MS	F	Significance F
Regression	5	0,119018402	0,02380368	1,822322873	0,10959049
Residual	217	2,83451342	0,013062274		
Total	222	2,953531822			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0,059865161	0,012342874	4,85017998	2,35225E-06	0,035537896	0,084192426	0,035537896	0,084192426
Asset Size	-0,016955707	0,017436841	-0,972407034	0,331930764	-0,051322957	0,017411544	-0,051322957	0,017411544
Op/Assets	0,010567258	0,068089702	0,155196119	0,87681097	-0,123634567	0,144769082	-0,123634567	0,144769082
Cap/Assets	1,114060351	0,611403512	1,822136003	0,069810848	-0,090989222	2,319109925	-0,090989222	2,319109925
Op/Assets x Assets	-8,01883E-13	4,59914E-12	-0,174355124	0,861748935	-9,86658E-12	8,26281E-12	-9,86658E-12	8,26281E-12
Cap/Assets x Assets	6,35757E-12	2,64778E-11	0,24010949	0,810472046	-4,5829E-11	5,85441E-11	-4,5829E-11	5,85441E-11

PRIVATE COMPANY REGRESSION RESULTS

1) Independent Variable: Capital Leas Value / Assets
Dependent Variable: Altman Z scores

Table 52

Regression Statistics	
Multiple R	0,011744677
R Square	0,000137937
Adjusted R Square	-0,014785377
Standard Error	5,127590983
Observations	69

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,243020899	0,243020899	0,009243083	0,923695617
Residual	67	1761,576682	26,29218929		
Total	68	1761,819703			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	1,386768867	0,661969149	2,094914648	0,039962395	0,065472931	2,708064804	0,065472931	2,708064804
X Variable 1	0,176217679	1,832909578	0,096140956	0,923695617	-3,482285107	3,834720465	-3,482285107	3,834720465

2) Independent Variable: Capital Leases as Dummy's
Dependent Variable: Altman Z scores

Table 53

Regression Statistics								
Multiple R	0,011744677							
R Square	0,000137937							
Adjusted R Square	-0,014785377							
Standard Error	5,127590983							
Observations	69							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0,243020899	0,243020899	0,009243083	0,923695617			
Residual	67	1761,576682	26,29218929					
Total	68	1761,819703						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	1,386768867	0,661969149	2,094914648	0,039962395	0,065472931	2,708064804	0,065472931	2,708064804
X Variable 1	0,176217679	1,832909578	0,096140956	0,923695617	-3,482285107	3,834720465	-3,482285107	3,834720465

3) Independent Variable: Altman Z scores
Dependent Variable: Capital Leases / Assets

Table 54

Regression Statistics	
Multiple R	0,004549547
R Square	2,06984E-05
Adjusted R Square	-0,014904366
Standard Error	0,055988209
Observations	69

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	4,34724E-06	4,34724E-06	0,00138682	0,970404355
Residual	67	0,210023528	0,00313468		
Total	68	0,210027875			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0,010587544	0,006997584	1,513028433	0,134975503	-0,003379693	0,024554781	-0,003379693	0,024554781
X Variable 1	4,96736E-05	0,001333877	0,037240033	0,970404355	-0,002612756	0,002712104	-0,002612756	0,002712104

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