STOCKHOLM SCHOOL OF ECONOMICS
Department of Accounting
Master's Thesis within Accounting and Financial Management
Spring 2014

Prediction of poor working capital development

Can poor working capital development be predicted using accounting based financial information?

Mikaela Hillman[1] and Marielle Borgström[2]

[1] 22006@student.hhs.se [2] 22036@student.hhs.se

Abstract

We investigate if accounting based financial information on an operating entity level can be used to predict poor working capital development (WCD) on a quarterly basis. The development is considered poor if the change in net working capital is not driven by an underlying change in customer orders, and hence poor in the sense that the development is unjustified. The study is performed using data from a Swedish multinational industrial company covering the period 2009-2013, resulting in 2,420 entity-quarter observations. The operating entities included are either customer centers (CCs) or production centers (PCs), where the main activity is selling for the former and manufacturing for the latter. The statistical method logit analysis is used to create three models. The model using all data results in a prediction power of 79.21%. Separating CCs and PCs, results in prediction powers of 81.10% and 76.90% respectively. Thus, prediction of poor WCD is possible using accounting based financial information in the form of key ratios. The key ratios found to have explanatory power to predict poor WCD are asset turnover, inventory intensiveness, asset structure, asset liquidity, an entity's historical frequency of poor WCD quarters, growth in equity and growth in debt. If the models are evaluated based on cost savings, the separate models are superior compared to the model estimated based on both CCs and PCs. The study performed is the first in its field in terms of predicting poor WCD and further research on the subject is encouraged.

Keywords: prediction model, logit analysis, working capital, working capital management, working capital development

Tutor: Kenth Skogsvik

Date: May 19, 2014

We would like to thank our case company enabling us to perform our study and for providing us with good thoughts and insights during the process. We would also like to thank our tutor Kenth Skogsvik for invaluable inputs and help throughout our research. You have always been available and provided us with guidance and support in critical moments. Thank you!

Table of Contents

1. Introduction

One of the most important issues on a company's agenda is proper working capital management (WCM) (EY, 2013). WCM impact both liquidity and profitability, two key factors ensuring a firm's survival and prosperity. From a liquidity point of view, a company needs to be able to meet its short-term obligations (Shin & Soenen, 1998; Raheman & Nasr, 2007). The timing of the operating cash flows, what we refer to as liquidity, is directly linked to the working capital. Inefficient management of the working capital could lead to financial distress, something that threatens the firm's survival. Money is a scarce resource and it is costly to run the normal day-to-day operations with external funds when internal funds are tied up in net working capital (Myers, 1984; Nobanee & AlHajjar, 2009). The higher likelihood of distress increases the required cost of capital, also, a build-up in net working capital is generally not followed by a compensating increase in operating income which results in a decreased profitability, both of which have a negative effect on firm value. The underlying objective of a firm is to maximize firm value (Jensen, 2001) and ensure a liquidity level sufficient to meet the short term obligations, which explains why efficient WCM is of such importance to firms. Although there seems to exist an understanding of the importance of efficient WCM within firms, they still seem to face challenges in this area.

We have investigated the perceived issues related to WCM in a Swedish multinational industrial company, which will serve as a case company for this study. What specifically concerns the company is that the operating entities tend to use external funds (funds provided by group treasury or banks) to finance poor working capital developments (WCDs). The development is considered unjustified, and hence poor, if the change in net working capital is not driven by an underlying change in customer orders. The company wishes to eliminate the funding provided in such a situation as it increases net working capital levels in the operating entities and allows them to be careless with regards to tie-up of internal funds in net working capital. However, group treasury cannot refuse to provide funding to the operating entities in a situation where the entities themselves cannot meet their external obligations. The solution is therefore not simply to stop provide funds when they are asked for.

Based on this perceived problem we see a demand for the ability to predict these funding needs and by doing so, be able to avoid them. Donaldson (1969) stresses the need to plan for the undesirable, but still probable, events when it comes to managing the flow of funds. He argues that by doing so, a company will prevent an unexpected need of funds to turn into a crisis for the company. Predicting the events that will require funding will enable the company to take actions before the event occurs and before the pressure of circumstances make actions difficult and costly (Donaldson, 1969). Being able to predict the funding need related to poor WCD would enable the company to take actions to prevent it and by doing so avoid the future funding need. Although the poor WCD may not be completely avoided, a prediction of the event will at least enable group treasury to plan the funding and by doing so make sure the funds will be readily available and avoid costs associated with the quick need for funds. Hence, there is not only a value in the ability to predict and plan the funding need in a company but also in terms of WCM, why we aim to create a model predicting poor WCD. We believe that similar working capital problems exist within other multinational industrial firms and that there is a demand for the ability to predict such a development in working capital even within other firms.

Accounting based financial information in the form of key ratios have been used in order to predict poor WCD, where asset turnover, inventory intensiveness, asset structure, asset liquidity, an entity's historical frequency of poor WCD quarters and growth in equity resulted in the model with the highest prediction power of 79.21%. Thus, there is prediction power in using accounting based financial information to predict poor WCD on a quarterly level for operating entities. Separate models, dividing the data on customer (selling) and production (manufacturing) centers (CCs and PCs), give slightly higher prediction power for CCs, but not significantly. However, if the models are evaluated based on cost savings, both separate models are superior compared to a model estimated based on both CCs and PCs. Our study is a first effort to predict poor WCD in academia and enable further research opportunities.

The paper is divided into nine parts; (1) below section covers purpose and scope of the study, (2-4) followed by theory, poor WCD definition and previous literature, (5) data and sample description, (6) statistical method used, (7) results and analysis and ending with (8-9) discussion of our results and conclusion.

1.1 Purpose

We investigate if it is possible to predict poor WCD (the development is considered unjustified, and hence poor, if the change in net working capital is not driven by an underlying change in customer orders) using accounting based financial information. Deterioration of financial ratios can reveal potential business crisis, which can be captured using financial data (Beaver, Kennelly & Voss, 1968). Bankruptcy prediction models have shown to have prediction power using accounting based financial information. Inefficient management of working capital can cause financial distress and threaten a firm's survival, and although bankruptcy is a more extreme event than poor WCD, we believe that a similar methodology as for bankruptcy prediction can be used for predicting poor WCD. Accounting based financial information is used by different groups; by owners for stewardship objectives, by investors for valuation and by managers for financial management purposes (Skogsvik, 2013). Our prediction model will enable managers to use the accounting based financial information in a new way for their management of working capital and the related financial planning. More specifically, accounting based financial information in the form of key ratios will be used as input in the model. Our model could prevent poor liquidity and profitability through detection of poor WCD in advance, in best case enabling the entity's manager to take appropriate actions to prevent the occurrence of the event or second best case enable time for financial planning at group treasury. The purpose of this study leads us to our *research question*;

Can poor working capital development be predicted using accounting based financial information?

The method used is called logit analysis, a multivariate statistical method where several variables together are used to predict the probability of an event. Establishing a model based on accounting based financial information which is easily accessible to the company facilitates the use of the model, and the output in the form of probabilities is understandable and communicable within the organization. The model aims to serve as a first step for the company to detect if the entity has inefficient WCM, in the form of poor WCD, which could result in illiquidity and low profitability (see e.g. Shin & Soenen, 1998; Deloof 2003; Garcia-Teruel & Martinez-Solano, 2007; Raheman & Nasr, 2007; Samiloglu & Demirgunes, 2008; Nobanee & AlHajjar, 2009; Zariyawati et al., 2009; Garcia, Martins & Brandão, 2011). The model could be used as a warning system, where the model estimates probabilities of poor WCD, which the company needs to discuss, understand and then decide what appropriate actions to take.

1.1.1 Scope

We have chosen to investigate if it is possible to predict poor WCD on a quarterly basis using accounting based financial information. Quarterly instead of monthly data is used as we consider one quarter a reasonable time to take actions for to prevent poor WCD. As working capital has been shown to be difficult to forecast (REL, 2012; EY, 2013), we only predict poor WCD one quarter in advance and not several quarters as we believe the prediction power will be low by doing so.

We have chosen to use operating entities within one single company instead of stand-alone firms. According to Hoshi et al (1991), stand-alone firms are more careful and cautious of liquidity levels as they do not receive support from a group that could save them in case of illiquidity. Belonging to a group has shown that entities tend to be more careless in terms of liquidity as external funds can more easily be provided through the group (Padachi, 2006). Therefore, we expect poor WCD to be common at operating entity level and as a result several entities with poor WCD will probably exist within the case company. We also expect these entities to have a more severe deterioration of key ratios prior to poor WCD compared to stand-alone firms. Both mentioned reasons could result in better prediction power. Also, using a case company enables us to customize the model taking into account its' specific business features to again, ensure best prediction power. Our case company is a Swedish multinational industrial company and the operating entities used for the study are customer centers (CCs) and production centers (PCs). The former's main activity is selling and the latter's manufacturing. We will create three models, one model estimated on data from all entities and two models where CCs and PCs are separated, as their activities differ and thus the prediction power might increase by separating them.

Previous studies on WCM evaluate actions' and policies' effect on liquidity and profitability, give suggestions on how working capital should be managed and how a company can release funds when having inefficient WCM. Note, many studies focus on appropriate actions when inefficient WCM has occurred, while our focus is to predict the probability of poor WCD, which is a form of inefficient WCM, before its occurrence. Our study does not aim to include what actions the operating entities should take to improve their current WCM or to avoid a future poor WCD. Neither do we aim to create a liquidity model estimating appropriate cash levels through financial optimization as some other studies have done (e.g. Baumol, 1952; Miller & Orr, 1966).

Many previous studies examine how the working capital components affect profitability (e.g. Shin & Soenen, 1998; Deloof, 2003; Eljelly, 2004; Padachi, 2006; Garcia-Teruel & Martinez-Solano, 2007; Raheman & Nasr, 2007; Samiloglu & Demirgunes, 2008; Nobanee & AlHajjar, 2009; Zariyawati et al., 2009; Gill, Biger & Mathur, 2010; Garcia, Martins & Brandão, 2011). We will not investigate the exact effect our model will have on an entity's profitability or liquidity. We will rather predict what probability an entity has of poor WCD as it is defined in section *Finding poor working capital development.*

2. Theory

Working capital is an important part of a company's total capital (EY, 2013) and consists of two parts; current assets and current liabilities. It is a measure of a firm's liquidity, where net working capital is defined as current assets minus current liabilities (Hansson, Arvidson & Lindquist, 2009; Sharma, 2009; Preve & Saria Allende, 2010). On the operational side, working capital primarily consists of three parts: accounts receivables, inventory and accounts payables (Koller, Goedhart & Wessels, 2010). Trade credit creates accounts receivables and accounts payables, and the production cycle results in build-up of inventory, components we hereafter refer to as working capital. Key ratios including the working capital components are valuable to assess a company's liquidity and financial strength (Sagan, 1955; Eljelly, 2004).

Working capital ties up cash and arises as a result of the timing difference of expenses and the matching income (Dong & Su, 2010). The timing problem can in some situations be avoided by using financial arrangements that either requires payment before delivery (i.e. online shopping) or deferral of payment of accounts payables until the matching income is received. However, the majority of productions require payment of expenses for inputs prior and during the production while income is collected first when the product or service is delivered (Chan, 2010).

2.1 Maximizing the value of the firm

One of the most fundamental theories is that a firm's objective should be to maximize profit and its long term firm value, a theory that has been developed during more than 200 years of economic research (Jensen, 2001). Jensen (2001) argues that this objective, although the existence of the opposing stakeholder theory, is what firms should evaluate its performance on in order to ensure efficient management of the firm. Related to this theory are different models where accounting based financial information is used to value a firm. These models are helpful in understanding the relationship between accounting numbers and firm value. One illustrative model useful to understand the effect net working capital has on the value of the firm, is the value added valuation (VAV) model. The model is based on the logic of summing the accounting book value of operating net assets (ONA), the present value of future abnormal operating earnings until the horizon point in time, and the present value of expected goodwill/badwill of ONA at the horizon point in time (Skogsvik, 2002). The VAV model is defined as:

$$\mathrm{V(ONA_0)} = \mathrm{ONA_0} + \sum_{t=1}^{T} \frac{(\mathrm{RONA_t} - \mathrm{r_{wacc}}) \times \mathrm{ONA_{t-1}}}{(1+\mathrm{r_{wacc}})^t} + \frac{\mathrm{ONA_T} \times \left(\frac{\mathrm{V(ONA_T)}}{\mathrm{ONA_T}} - 1\right)}{(1+\mathrm{r_{wacc}})^T} \qquad (1)$$

where

$\mathrm{V(ONA_0)}$ = Value of invested capital in the firm at time $t = 0$

$\mathrm{ONA_0}$ = Operating net assets at $t = 0$

= Operating assets – Operating liabilities at time $t = 0$

= Book value of owner's equity + Financial net debt at time $t = 0$

Financial net debt (ND) is defined as debt minus financial assets at time $t = 0$

$\mathrm{V(ONA_T)}$ = Expected value of invested capital in the company at the horizon point in time $t = T$

$\mathrm{ONA_{t-1}}$ = Book value of operating net assets at $t = t - 1$

$$\mathrm{RONA}_t = \frac{\mathrm{OI}_t \times (1 - \mathrm{T}_C)}{\mathrm{ONA}_{t-1}}$$

OI_t = Operating income at time $t = 0$

T_c = Tax rate

r_{wacc} = Weighted average cost of capital after taxes

$= r_E \times (1 - L) + r_{ND} \times (1 - T_C) \times L$

where

r_E = required rate of return on owner's equity

r_{ND} = required rate of return on company financial net debt

L = company target leverage ratio = $V(ND_t) / V(ONA_t)$

(Skogsvik, 2002)

Working capital is part of ONA and thus affects profitability (RONA). As illustrated by the valuation model, theory suggests that in order to maximize the value of the firm, net working capital should be as low as possible for a given level of RONA. Low levels of net working capital have also empirically been shown to increase firm value (Nazir & Afza, 2009). The majority of empirical studies on working capital in relation to profitability have come to the conclusion that lower levels of net working capital are associated with a higher profitability (e.g. Shin & Soenen,1998; Deloof, 2003; Garcia-Teruel & Martinez-Solano, 2007; Raheman & Nasr, 2007; Samiloglu & Demirgunes, 2008; Nobanee & AlHajjar, 2009; Zariyawati et al., 2009; Garcia, Martins & Brandão, 2011) The negative effect that a net working capital increase has on profitability (RONA), indicates that an increase in ONA due to increased net working capital is normally not followed by a compensating increase in operating income, i.e. companies cannot charge their customers for their increased level of net working capital. Inefficient WCM that turns into liquidity issues and higher likelihood of financial distress will cause a higher required weighted average cost of capital which also has a negative effect of firm value. With regards to firm value maximization, efficient WCM is to ensure lowest net working capital level for a given level of profitability.

If working capital would not affect profitability, firm value would be maximized if having no working capital. However, working capital does affect profitability due to the existence of business praxis of trade credit and timely delivery. At some low levels of net working capital, a trade-off exists between lower net working capital and revenue; a large inventory decrease stock-out risks and ensure on-time delivery (Sagan, 1955), and extending payment periods may entice buyers (Dewing, 1941; Fazzari & Petersen, 1993). Eliminating inventory would probably cause production difficulties and delayed deliveries resulting in unsatisfied customers and in turn a harmed profitability. Net working capital also affects liquidity as higher levels are associated with a longer cash conversion cycle (CCC). This in turn affects a firm's ability to meet its short term obligations and net working capital therefore affects the likelihood of financial distress. With regards to accounts receivables and accounts payables, they could be eliminated if a bank credit market for working capital existed. This would mean that the bank would act as a third party and companies would then get paid at delivery and accounts payables would be replaced by bank loans. The tie up of cash will decrease but at the expense of interest costs. Such a bank loan solution for trade credit does however not exist. According to Burkart & Ellingsen (2004), the existence of trade credit and thus accounts receivables and accounts payables is due to asymmetric information making banks unwilling to lend. They argue that suppliers are more willing to lend money and extend payment periods to their customers, as they know that the material bought will be used in production and generate revenues for the customer. When banks lend money to companies, they do not know how the money will be spent to the same extent as suppliers do. A bank credit market to eliminate accounts receivables and accounts payables is not a likely solution. Though, a somewhat similar service known as factoring exists, but it has not been used to the extent that accounts receivables have been eliminated. Hence, we conclude that working capital will continue to exist as the elimination will hurt profitability and in turn firm value. This means that the suggestion that lower levels of net working capital increases firm value is only valid as long as the low level does not hurt profitability and thus firm value maximization (shown in e.g. Deloof, 2003; Afza & Nazir, 2007; Garcia, Martins & Brandão, 2011).

Also, the pecking order theory is in line with firm value maximization. The pecking order theory suggests that internal funds should be used before external debt and equity issue when in need of cash, as it is the cheapest source of funds and are readily available to the firm (Myers & Majluf, 1984). Equity issue is seen as the most expensive source of external financing since managers are assumed to have asymmetric information; an equity issue signal overvaluation to investors which affects the firm negatively (ibid). External source of funds, which may not even be available to the firm, are often associated with higher costs compared to the use of internal funds due to transaction costs, agency problems and asymmetric information (Fazzari & Petersen, 1993). If a firm is financially constrained, internal funds are the only source to finance investments and if too much capital is tied up in net working capital it will hurt future growth of the firm and thus lower firm value (ibid; Chan, 2010). By keeping a low net working capital level, a company can avoid tying up unnecessary cash which then instead can be used for investments, enabling higher profitability and firm value. However, optimized leverage enables the firm to utilize the tax shield optimally which increases the value of the firm in theory, this would change the pecking order when optimal level of leverage has not been reached, i.e. external debt could be a better option than internal funds in such a situation.

The pecking order theory illustrates the importance of avoiding unnecessary tie up of cash in net working capital. WCM affects profitability and firm value but it also directly impacts a firm's liquidity, which will be covered in the next section.

2.2 Liquidity

As mentioned, cash released from net working capital is the least costly source of funds (Myers, 1984; EY, 2013), and are funds a company does not afford to overlook (EY, 2013). Liquidity according to the International Accounting Standards Board (IASB) reflects the asset or liability's nearness to cash (IASB, 2007). A common measure of liquidity and its relation to net working capital is the CCC (Garcia, Martins & Brandão, 2011), see equation (2). DSO measures the collection period of sales, DIO the time it takes to convert the inventory to sales and DPO captures the number of days the company is able to defer payment to suppliers (Cagle, Campbell & Jones, 2013).

$$\mathrm{CCC} = \text{Cash Conversion Cycle} = \mathrm{DSO} + \mathrm{DIO} - \mathrm{DPO} \tag{2}$$

where

$$\mathrm{DSO} = \text{Days Sales Outstanding} = \frac{(\text{Accounts receivables}_{\mathrm{t}} + \text{Accounts receivables}_{\mathrm{t-1}})/2}{\text{Revenues}/365}$$

$$\mathrm{DIO} = \text{Days in Inventory Outstanding} = \frac{(\text{Inventory}_{\mathrm{t}} + \text{Inventory}_{\mathrm{t-1}})/2}{\text{Cost of goods sold}/365}$$

$$\mathrm{DPO} = \text{Days Payable Outstanding} = \frac{(\text{Accounts payables}_{\mathrm{t}} + \text{Accounts payables}_{\mathrm{t-1}})/2}{(\Delta\text{Inventory}_{\mathrm{t}} + \text{Cost of goods sold})/365}$$

(Sharma, 2009)

More generous payment terms to customers means less liquid accounts receivables and is captured by a longer CCC. A high DPO means many days of interest free financing, something that results in a shorter

CCC and a slow moving inventory results in longer CCC (Cagle, Campbell & Jones, 2013). A shorter CCC means quicker cash conversion and thus a better liquidity and net working capital position in the company (ibid). From liquidity point of view, the shorter the CCC the more efficient WCM. This view of WCM is in line with the theory of value maximization; low levels of accounts receivables and inventory and high levels of accounts payables results in higher firm value. However, suppliers can use higher prices to make sure that they are compensated for the credit period. Also, as discussed earlier, lowering net working capital too much could hurt profitability (see e.g. Padachi, 2006; Mathuva, 2010; Nazir & Afza, 2009: Nobanee & AlHajjar, 2009). Shorter CCC can lead to costs associated with the risks of declining revenues while a longer CCC is associated with costs related to tie up of cash in net working capital (Nobanee, 2009). At a certain level there is a trade-off between liquidity and profitability, which also have been empirically confirmed (e.g. Shin & Soenen, 1998; Deloof, 2003; Eljelly, 2004; Raheman & Nasr, 2007; Mathuva, 2010; Zariyawati et al., 2009; Dong & Su, 2010). When investigating the correlation between CCC and profitability, studies find both negative and positive correlations; i.e. short CCC improves profitability and thus liquidity and no trade-off exists, while a long CCC that gives better profitability is at the expense of liquidity. It seems as if the trade-off between liquidity and profitability only exists when CCC has been pushed to a certain level which is the reason for contradicting results from previous research. When a shortening of the CCC has a negative effect on profitability, it will also have a negative effect on firm value which is illustrated by the VAV model.

Another common approach used to measure liquidity is the current ratio and variations of this measure such as the quick ratio exist (Eljelly, 2004; Cagle, Campbell & Jones, 2013). Current ratio is defined as current asset divided by current liabilities, where a ratio of one means that the firm has enough liquid funds to cover its current liabilities (Sharma, 2009). Based on this measure of liquidity, it would be preferable to have high levels of accounts receivables and inventories and low levels of accounts payables in order to ensure good liquidity in terms of a high current ratio. This contradicts to what the CCC measure of liquidity define as good and the explanation lies in that the current ratio does not take into account the time it takes to convert the assets into money (Cagle, Campbell & Jones, 2013). A lower level of current ratio is generally regarded as unfavorable but in terms of net working capital it could rather indicate efficient WCM (ibid). Improving liquidity measured as the current ratio would not ensure value maximization and cannot be considered to be efficient WCM; a higher current ratio has a negative effect on profitability, which has also been empirically shown (e.g. Eljelly, 2004). The quick ratio excludes inventories from current assets as it is seen as less liquid (Burkart & Ellingsen, 2004; Eljelly, 2004). The quick ratio as a measure of liquidity is more in line with liquidity measured as CCC and the theory of value maximization as the ratio does not suggest that high levels of inventory are preferable, however, it still fails to capture the time of cash conversion when it comes to accounts receivables and accounts payables.

We can conclude that CCC is an appropriate liquidity measure to use in relation to WCM as it takes into account the time it takes to convert net working capital into cash and is the liquidity measure that is in line with the theory of value maximization. Also, it is the measure that is most commonly used as a proxy for WCM. Therefore we have chosen to use CCC as the definition of liquidity in this paper.

2.3 Poor working capital development and its impact on firm value

The theory of value maximization suggests lowest possible net working capital for a given level of profitability. Inefficient WCM can therefore be defined as having other than optimal net working capital levels in terms of firm value maximization. In this paper we try to predict the undesirable event called poor WCD, a perceived working capital problem in our case company. The company wants to avoid using external funds (funds provided by group treasury or banks) to finance poor WCDs. A WCD is considered unjustified, and hence poor, if the change in net working capital is not driven by an underlying change in customer orders.

Working capital is often assumed to change in proportion to changes in revenues (Koller, Goedhart & Wessels, 2010), which supports the approach of linking WCD to customer orders. If an entity has an increased demand for its products, cash to be received from accounts receivables belonging to previous sales will be insufficient to cover the increased outflow needed for the increased production. Hence, growth in customer orders may create a funding need for the entity for a build-up of net working capital that is not value destroying. In such a situation, entities should not be considered to have inefficient WCM just because they finance a build-up of net working capital with external funds. This misclassification can be avoided by relating the WCD to the underlying change in orders.

An entity in need of external funding due to an unjustified WCD is said to have poor WCD. The development can be said to be poor as it is value destroying. Higher net working capital levels resulting in lower profitability and worse liquidity will have a negative effect on firm value as previously discussed in relation to the VAV-model. If the company is financially constrained, firm value could also decrease from the inability to invest in value creating assets as funds are used to finance net working capital. Further, if using external funds to finance the build-up of net working capital, increase the negative effect on firm value, as suggested by the pecking order theory. An unjustified net working capital build-up financed with external funds is value destroying in several aspects and can be said to be inefficient WCM, which explains why it is said to be a poor WCD.

Just like a build-up in net working capital that is not supported by an increase in orders can be considered to be a poor WCD, a lack of reduction in net working capital when orders decrease is also considered a poor WCD. In such a scenario net working capital should be reduced in order to avoid negative effects on profitability and firm value, and from the liquidity point of view, the company needs to reduce its tie-up of cash in net working capital to avoid a worse liquidity position.

Poor WCD is aimed to capture when net working capital increases although orders do not, but also when orders decrease and net working capital do not follow. Both of these scenarios are value destroying and can be said to result from inefficient WCM. However, inefficient WCM occurs as soon as net working capital deviates from what is value maximizing. Poor WCD is inefficient WCM, although inefficient WCM has a broader meaning than just poor WCD.

2.3.1 Finding poor working capital development

Our model have two outcomes, the entity is either classified as having poor WCD or non-poor WCD a certain quarter. In order to be able to classify an entity as poor or non-poor, we need to establish an approach for how to separate poor and non-poor WCD entities. Poor WCD is likely to result in a funding need if it is related to a build-up of net working capital not supported by an increase in orders or a failure to release funds through decrease in net working capital when decline in orders. An approach to find entities with poor WCD is thus by looking at the inflows and outflows of funds in relation to changes in net working capital.

External funding can be in the form of financial debt or equity and is according to the pecking order theory the most value destroying sources of funding. It should thus be avoided to finance poor WCD with debt and equity. We have chosen to extend the undesired funding sources to include financial assets. If debt and equity is considered inappropriate to finance poor WCD, the same argument should be used for financial assets, even though it technically is internal funds it should rather be used for investments, dividends or amortizations following the theory of value maximization. External funding in this paper is therefore referred to as both debt and financial assets, as equity funding is not possible on an operating entity level. The financial assets in our case company constitute solely of cash and cash equivalents, of which we have chosen to classify two percent of revenues as operating cash (Koller, Goedhart & Wessels, 2010).

The operating entities cannot directly obtain funding through equity, the funding sources left is through changes in debt (borrowing from group treasury is seen as external debt from the entities' perspective) or changes in financial assets, i.e. changes in net debt. The funding need in a company according to Penman (2013) (see Appendix 1) can be rewritten as:

$$\Delta ND_t = Inv_t + \Delta(\text{net WC})_t - [OI_t(1 - T_c) + Depr_t - (r_{ND} * ND_t)(1 - T_c)] + DIV_t \qquad (3)$$

where

Inv_t = Net cash investments in assets not included in net working capital at time t

$\Delta(\text{net WC})_t$ = $\Delta(\text{Net working capital}_t)$ = $(\text{net WC}_t - \text{net WC}_{t-1})$

= Δ(Operating current assets – Operating current liabilities) at time t

OI_t = Operating income at time t

$Depr_t$ = Depreciation at time t

r_{ND} = Interest rate on net debt

ND_t = Net debt at time t = (Debt-Financial assets) at time t

T_c = Tax rate

DIV_t = Dividends at time t

Rearrangement of formula (3):

$$\Delta(\text{net WC})_t - [OI_t(1 - T_c) + Depr_t - (r_{ND} * ND_t)(1 - T_c)] = \Delta ND_t - Inv_t - DIV_t \qquad (4)$$

Equation (4) illustrates that an increase in net debt that has not been used to finance investments or dividends ($\Delta ND_t - Inv_t - DIV_t > 0$), has been used to finance an increase in net working capital that could not be financed by the operating cash flows minus cash flows from net interest costs after tax ($\Delta(\text{net WC})_t - [OI_t(1 - T_c) + Depr_t - (r_{ND} * ND_t)(1 - T_c)] > 0$).

If a WCD is poor or non-poor depends on the underlying changes in orders. In the case company, the CC receives the order from the customer and forwards it directly to the PC. If the PC operates at full capacity it is reasonable to assume that the average time period between an order received and finished product is about two quarters. The finished product is at that point sent to the CC, which pays the PC for the product and increases its net working capital first two quarters after the order was received. As the PCs make the major and more costly investments at the end of the production cycle, the time lag between orders received and net working capital increase is normally about the same for PCs as for CCs. Therefore, a change in orders is normally shown as a change in net working capital after two quarters both for CCs and PCs, which also means that a funding need arises two quarters after the growth in orders.

An increase in net working capital explained by an increase in orders should not be considered as poor WCD. Therefore, poor WCD is defined as:

$$\Delta \mathrm{ND_t} - \mathrm{Inv_t} - \mathrm{DIV_t} - \Delta \mathrm{Orders} > 0 \ \rightarrow \text{poor WCD} \tag{5}$$

where

$\Delta \mathrm{Orders_t} = \mathrm{Orders_{t-2}} - \mathrm{Orders_{t-3}}$

$\Delta \mathrm{ND_t}$ is deducted by $\Delta \mathrm{Orders_t}$ in order to capture the acceptable increase of funds due to an increase in orders. A decrease in orders should lead to a decrease in net working capital. In order not to be classified as poor, the entity should have decreased its net working capital with the amount corresponding to the decline in orders. The release of funds should then have been used for amortization, raise financial assets, investments or dividends, something that is captured by using the definition in formula (5).

Our model will predict what probability an entity has of poor WCD one quarter in advance. An entity with a high probability of poor WCD the coming quarter, i.e. the entity has a high likelihood to finance unjustifiable growth in net working capital or failing to release internal funds. Not only would it prolong the entity's CCC in relation to operating income, but also indicate poor liquidity one quarter ahead as it is likely that the entity is in need of funds due to poor WCD. Thus, poor WCD normally means poor liquidity. A short CCC ensures better liquidity and lower net working capital level. Furthermore, it is value maximizing and has shown to increase profits (e.g. Shin & Soenen, 1998; Deloof, 2003; Garcia-Teruel & Martinez-Solano, 2007; Raheman & Nasr, 2007; Samiloglu & Demirgunes, 2008; Nobanee & AlHajjar, 2009; Zariyawati et al., 2009; Garcia, Martins & Brandão, 2011). Our approach to separate poor and non-poor entities each quarter in terms of poor WCD could prevent worse liquidity in terms of longer CCC and thus also a lower profitability.

2.3.1.1 Limitations in capturing entities with inefficient working capital management

Some limitations exist with our definition of poor WCD. By focusing on entities with poor WCD we only capture part of all entities that have inefficient WCM. An entity with other than optimal level of net working capital has inefficient WCM. If the entity has a non-maximizing net working capital level but no need to finance a build-up of net working capital with external funds, or if it does not fail to release internal funds when orders decrease, the entity will not be detected in the model. We also miss to classify entities as poor that are profitable enough to finance what may be an unjustified build-up of net working capital through operating cash flows minus cash flows from net interest costs after tax, as illustrated in equation (6).

$$\Delta(\text{net WC})_t - [\text{OI}_t(1 - \text{T}_c) + \text{Depr}_t - (\text{r}_{\text{ND}} * \text{ND}_t)(1 - \text{T}_c)] < 0 \quad (6)$$
$$\rightarrow \text{profitability is so high that it covers an unjustified build up of net working capital}$$

Some entities classified as poor could be entities hit by extreme or unexpected events, e.g. an inventory fire or natural disaster, and thus are entitled to use external funds to finance a build-up of net working capital, i.e. the build-up is not due to inefficient WCM. By excluding extreme values of the key ratios, we hope to eliminate such extreme situations and thus should decrease the impact the values could have on the results.

The approach chosen to find poor and non-poor entities is based on the assumption of an average time lag for our case company's products in a normal business environment. However, the time lag between orders received and net working capital varies dependent on the product and on the business situation. Hence, entities with a time lag deviating from the assumption will be misclassified as the matching order to the change in net working capital is not found two quarters prior to the change.

As discussed earlier, using external funds to finance poor WCD is not value maximizing and could decelerate growth due to lower investment levels if the company is financially constrained, and thus firm value decreases (Fazzari & Petersen, 1993; EY, 2013). However, Sagan (1955) means that sometimes a firm need to use external funds to finance poor WCD if it is estimated to benefit the company long-term. A build-up of inventory will affect a firm's liquidity negatively but may be beneficial for future growth or utilization of economies of scale and lower input prices. By our definition, an entity will be classified as poor when in fact external funds are used for future success. An entity classified as poor has a high probability of poor WCD, thus, using external funds to finance net working capital even though they might not be "poor" if using external funds for above reason. Our aim is to create a model that predicts when an entity has a high probability of poor WCD, i.e. using external funds for net working capital growth when in fact no actual growth in orders exists or failure to release funds through decrease in net working capital when a decline in orders. Hence, indirectly the model enable prediction of entities in need of external funds and thus capture liquidity issues which normally inefficient WCM creates. The model is a first step for the company to identify the operating entities that have high risk of poor WCD and thus needing external funds. The model could be used as a warning system, where each entity has the opportunity to evaluate what decisions to take and include strategic aspects, which our model unfortunately does not cover.

3. Empirical evidence on working capital's impact on profitability

There are several ways to analyze working capital and its management (Smith, 1973). Previous studies of working capital primarily investigate its impact on profitability. The working capital components (accounts receivables, inventory and accounts payables) affect both profitability and liquidity. Below sections discusses these variables and its impact on profitability based on empirical evidence. The studies use different measures of profitability, such as return on assets (ROA), return on net assets (RONA), and return on investment (ROI) for example. As in previous studies, we compare their results despite different profitability measures.

3.1 High accounts receivables and inventory affects profitability negatively

Managers can create value for their shareholders if the firms manage their working capital in more efficient ways by reducing accounts receivables and inventory to a reasonable minimum. Several studies have shown that high levels of accounts receivables and inventory are associated with lower profitability (e.g. Deloof, 2003; Padachi, 2006; Garcia-Teruel & Martinez-Solano, 2007; Raheman & Nasr, 2007; Falope & Ajilore, 2009; Nobanee & AlHajjar, 2009; Gill, Biger & Mathur, 2010; Garcia, Martins & Brandão, 2011). These variables are also associated with longer CCC and thus a worse liquidity position. Companies shortening their accounts receivables often do so due to shortage of money as a result of a weak liquidity position (Meltzer, 1960).

Mathuva (2010) investigated working capital's effect on profitability for 30 companies listed on the Nairobi Stock Exchange from 1993 to 2008, using Pearson and Spearman's correlations, the Pooled Ordinary Least Square (OLS) and the fixed effects regression models. DSO was found to have a highly significant negative effect on profitability. The relationship between DIO and profitability was however found to be positive and significant, which contradicts previous studies' results. Gill, Biger & Mathur (2010) did not even find a significant relationship between DIO and profitability. One possible reason to why empirical results differ are due to the trade-off that arises at a certain level of CCC; i.e. where costs of interrupted production due to inventory shortage are more costly than the cost of holding extra inventory (Sagan, 1955; Deloof, 2003).

3.2 Less profitable firms have high levels of accounts payables

Many studies show that there is a negative relationship between accounts payables and profitability (e.g. Deloof, 2003; Raheman & Nasr, 2007; Falope & Ajilore, 2009). The empirical results contrast the theory of value maximization; firms with lower net working capital, which can be achieved by higher accounts payables, have higher profitability and firm value. A possible explanation to the observed relationship in the studies is that less profitable firms have relatively higher accounts payables as they wait longer to pay their bills (Petersen & Rajan, 1997; Deloof, 2003). Higher accounts payables results in a shorter CCC which generally indicate efficient WCM but in these cases it rather signals illiquidity and inefficient WCM. Although most studies found a negative relationship, Nobanee & AlHajjar (2009) show other results. The authors analyzed a sample of 2,123 Japanese non-financial companies listed on the Tokyo Stock Exchange for the period 1990-2004 and concluded that managers can increase profitability by extending the accounts payable period. Mathuva (2010) reaches the same results. This is also in line with Nazir & Afza's (2009) findings of higher levels of current liabilities increase the value of a firm, which is supported by the theory of value maximization. Deferral of payments to suppliers enables companies to access to the material before paid and is a cheap source of financing. However, late payments can have a high implicit cost whenever early payment discounts are available. Though, paying suppliers in advance due to discounts also lowers accounts payables and thus increase net working capital, and create potential liquidity risks (Dewing, 1941; Fazzari & Petersen, 1993; Gill, Biger & Mathur, 2010). Managers should be careful extending the payables deferral period as it could damage the company's credit reputation and harm profitability in the long-run (Garcia, Martins & Brandão, 2011).

3.3 Shorter CCC affects profitability positively

Zariyawati et al. (2009) studied the relationship between CCC, used as a proxy for WCM, and profitability. He used company-year panel data the period 1996-2006 for companies listed in Bursa Malaysia, resulting in1,628 observations. Using Pooled OLS regression, they found a highly significant negative relationship between CCC and profitability, i.e. reduction of the CCC is associated with higher profitability. Managers should strive to reduce CCC until the optimal levels in terms of value creation are reached as it increases companies' efficiency of internal operations and results in higher profitability and firm value (Garcia, Martins & Brandão, 2011). Zariyawati et al.'s (2009) results are in line with many previous studies (e.g. Garcia-Teruel & Martinez-Solano, 2007; Raheman & Nasr, 2007; Samiloglu & Demirgunes, 2008; Nobanee & AlHajjar, 2009; Garcia, Martins & Brandão, 2011).

Shin & Soenen (1998) also studied WCM's impact on profitability using the net trade cycle (NTC). NTC is calculated as CCC but the three components are expressed as percentage of revenues, and the measure capture the changes in working capital needed as a result of changes in revenues. The relationship was studied through correlation and regression analysis using a large sample of listed American firms from the period 1975-1994. The relationship between NTC and profitability was strongly negative and they also found that a shorter NTC is associated with a higher risk-adjusted stock return and thus a higher firm value, which is in line with the theory of value maximization. Also, as they found a negative relationship between total liabilities and firm value they concluded that the positive effect from a shorter NTC on firm value comes from lower DSO and DIO rather than longer DPO. Deloof (2003) also concluded that manages can increase the profitability of the firm by reducing DSO and DIO to reasonable minimums based on his finding of a negative correlation between CCC and profitability.

Eljelly (2004) investigates if efficient liquidity management, i.e. managing current assets and current liabilities in a way that eliminates the risk of inability to meet short-term obligations, increase profitability. To do so, he examines the correlation between liquidity indicators and profitability. The data used is a sample of 29 listed Saudi Arabian companies from year 1996 to 2000. He finds a significant negative relationship between current ratio and profitability, however no significant relationship between CCC and profitability was found. This strengthens previous argument that current ratio and CCC measures liquidity in different ways.

3.4 Longer CCC impacts profitability positively

Although most studies have found a negative relationship between CCC and profitability, there are some studies that have found the opposite. Padachi (2006) investigates 58 Mauritian small manufacturing firms using panel data for the period 1998-2003 and finds a positive correlation between profitability and CCC. Gill, Biger & Mathur (2010) found similar results, i.e. longer CCCs impact profitability positively. Suggested explanations to the positive correlation are that higher levels of inventory might increase revenues due to decreased stock-out risks or that revenues could increase due to longer payment periods given to customers (Sagan 1955; Long, Maltiz & Ravid, 1993; Deloof & Jegers, 1996; Padachi, 2006).

The reason for different empirical results could be that the studies which found a positive correlation between CCC and profitability were made on firms which pushed their CCCs to shorter levels than optimal. Although a shorter CCC improves liquidity it could harm profitability, and if the trade-off level has been reached, opposite results to those studies performed where firms have not reached the trade-off level are expected. I.e. if firms are beyond the trade-off level in terms of too short CCC, it should increase its CCC to increase profitability, though at the expense of its liquidity.

4. Bankruptcy prediction models

Inefficient WCM increases the risk of financial distress, where poor WCD is one form of inefficient WCM. Prediction of bankruptcy has shown to have predictive power. Studies investigate the predictive ability from one year prior to bankruptcy up to commonly three years, but also more, to predict the event of bankruptcy. The early bankruptcy studies (e.g. Altman, 1968; Beaver 1966) used accounting based financial information to predict bankruptcy and later studies have continued to use similar information as input (e.g. Edmister, 1972; Altman, 1973; Blum, 1974; Altman et al.,1977; Ketz, 1978; Ohlson, 1980; Mensah, 1983; Zavgren, 1985; Skogsvik, 1988a), even till today (e.g. Dewaelheyns & Van Hulle, 2006; Leal & Santos, 2007). Empirical results show that accounting based financial information can be used to predict bankruptcy, and even though bankruptcy can be seen as a more extreme event compared to poor WCD, we will use accounting based financial information to investigate the possibility to predict poor WCD.

Various statistical methods have been used in past bankruptcy prediction studies, where the ones with probabilistic estimates of bankruptcy are the most interesting to us as we aim to predict the probability of poor WCD. We find it interesting to present some results using this method in order to verify and compare their prediction powers to our results, even though the event of bankruptcy is more extreme and thus a higher prediction power is expected. However, as proportions of bankrupt and surviving firms differ in the studies, and the prediction power depends on the weighting of these proportions, the prediction powers among studies cannot be compared. Though, adjusting the weight to similar proportions among studies, results are comparable. Skogsvik (1988a) presents adjusted results from previous studies performed. Ohlson (1980) used industrial companies from the database *COMPUSTAT* the period1970-1976 to predict bankruptcy, resulting in a prediction power of 85.00% when predicting the event one year in advance. Skogsvik (1988a) performed a study based on Swedish industrial companies. He tried to predict bankruptcy from one year up to six years ahead where the one year model had the highest prediction power of 83.30%. Interestingly, even six years before the event of bankruptcy a prediction power of 73.30% is reached, indicating that deterioration in key ratios can be found even six years prior to bankruptcy.

As it has been possible to predict bankruptcy several years prior to the event using accounting based financial information, deteriorated performance in key ratios is shown early. In the event of bankruptcy, key ratios likely differ more between bankrupt and surviving firms prior to the event than for poor and non-poor WCD entities. Thus, as mentioned, bankruptcy is a more extreme event than poor WCD and we therefore expect our prediction model to have lower prediction power compared to the bankruptcy prediction models.

5. Data and sample description

Quarterly data on operating level from year 2009-2013, treating each entity-quarter as an observation, resulted in a starting data set of 6,059 observations, of which 4,357 were CCs and 1,702 PCs. Each observation is classified as poor or non-poor based on how we separate the entities in terms of WCD. The classification is made in one quarter, time t, and the key ratios used as dependent variables for prediction are at t-1, i.e. the quarter prior to t.

Change in orders, which is needed for separation of poor and non-poor entities, requires data from t-1 to t-4. Therefore, entities can be classified as poor or non-poor from the first quarter in 2010 to the fourth quarter in 2013. Of 5,603 observations, the data consists of 3,477 non-poor and 2,126 poor. As we predict poor WCD one quarter before its occurrence, there need to exist a non-poor entity-quarter observation before the event. Therefore, for entities classified as poor several quarters in a row, the first poor entity-quarter observation is the only observation not excluded. Also, observations have been excluded due to missing data that was needed for the calculation of one or several of the key ratios used as dependent variables.

The final data set constitutes of 2,420 observations, 1795 (74.17%) non-poor and 625 (25.83%) poor. Of these, 1,736 observations are CCs of which 25.35% (74.65%) poor (non-poor) and 684 PCs of which 27.05% (72.95%) poor (non-poor). As proportions among poor and non-poor are similar for CCs and PCs, the occurrence of poor WCD among the two activities is very similar.

The frequency of poor entity-quarters is about the same for the entities (see Appendix 2, table 1). The proportion of poor and non-poor entities is evenly distributed across years and quarters, for both CCs and PCs (see table 5.1 and 5.2). Thus, neither seasonal effects nor extreme years seem to exist, indicating that the proportions are representative for the population. Therefore it is likely that around 26% of the entities will be poor going forward as well. Our sample proportions of poor and non-poor entities can therefore be assumed to be representative to the population's proportions.

Table 5.1

Proportions of non-poor and poor entities per year

	All Entities		CC		PC	
Year	Non-Poor	Poor	Non-Poor	Poor	Non-Poor	Poor
2010	0.7421	0.2579	0.7435	0.2565	0.7379	0.2621
2011	0.7517	0.2483	0.7546	0.2454	0.7440	0.2560
2012	0.7431	0.2569	0.7483	0.2517	0.7308	0.2692
2013	0.7306	0.2694	0.7398	0.2602	0.7090	0.2910

Table 5.2

Average proportions of non-poor and poor entities per quarter

	All entities		CC		PC	
Quarter	Non-Poor	Poor	Non-Poor	Poor	Non-Poor	Poor
q1	0.7395	0.2605	0.7386	0.2614	0.7431	0.2569
q2	0.7562	0.2438	0.7590	0.2410	0.7485	0.2515
q3	0.7499	0.2501	0.7721	0.2279	0.6948	0.3052
q4	0.7223	0.2777	0.7153	0.2847	0.7374	0.2626

The proportions of poor and non-poor entities per quarter each year are presented in Appendix 2, table 2.

6. Method

In order to predict poor WCD, three things need to be considered; (1) what key ratios to use as input, (2) decide on appropriate statistical method and (3) how to evaluate the models' prediction power, things that are covered in below section.

6.1 Using accounting based financial information

The initial selection of what key ratios to test in the three models is of extra importance; if key ratios that might be explanatory are left out, the models might not achieve highest possible prediction power (Skogsvik, 1988a). It is difficult to a priori know what key ratios will have statistical importance in the models, especially when no former studies have tried to predict poor WCD. Instead of testing a very large set of possible key ratios, we use the results from a principal component analysis (PCA) performed on a wide set of possible key ratios. PCA is a technique to transform a large data set of interrelated variables into a smaller number of derived variables, called principal components which are linear combinations of the original variables (Jolliffe, 2005). Selecting one key ratio from each component limits the initial selection of key ratios but still ensures preservation of the variation inherent in the larger data set (ibid), 2005). Furthermore, it restricts correlation among variables which is preferable when using a multivariate model (Skogsvik 1988a). Skogsvik (1988a) performed a PCA on an extensive data set of 71 key ratios that was derived to capture the variation inherent in the accounting based financial information available in financial statements. The PCA resulted in 17 principal components and Skogsvik (1988a) chose one key ratio from each principal component to use as the initial selection of key ratios in order to estimate a bankruptcy prediction model. We use the same selected ratios as Skogsvik (1988a) for our initial selection and by doing so we are confident in selecting key ratios that captures a wide range of information while minimizing correlation (see table 6.1).

Table 6.1

The initial selection of key ratios

Variable	Component	Definition
ROA	Operating profitability	(Earnings before taxes and interest expenses)/All assets
ROE	Profitability owners' equity	(Net income + depreciation + (-) non-recurring expenses (income)) / (Owners' equity and deferred taxes)*
rd	Interest expense	Interest expenses/(All liabilities and deferred taxes)*
tax	Tax expense	Income taxes/Earnings before taxes
assetturn	Asset turnover	Revenues/All assets
invint	Inventory intensiveness	Inventory/Revenues
cashpos	Cash position	Cash and cash equivalents/(Current liabilities – Advance payments)
shortliq	Short-term liquidity	Current assets/Current liabilities
assetstruct	Asset structure	Non-current assets/All assets
assetliq	Asset liquidity	(Non-current assets + Inventory)/All assets
size	Size	ln(All assets)
businessg	Business growth	Growth current liabilities/Current liabilities
geq	Growth Owners' equity	Growth owners' equity and deferred taxes/Owners' equity and deferred taxes
gdebt	Growth liabilities	Growth interest-bearing loans/Interest bearing loans
finstruct	Financial structure	Owners' equity and deferred taxes/All assetss

*Average of opening and closing balance

However, we choose to add some ratios we believe could be helpful in predicting poor WCD (see below for definitions). For efficient WCM, a decline in orders should be followed by a decrease in net working capital, and thus the variable orders could be helpful in predicting poor WCD. Due to the time lag mentioned in the section *Finding poor working capital development*, change in orders received is calculated using t-2 and t-3. If poor entities have higher likelihood to be poor also in the future, the variable poorWCDfreq is included to see if it could have explanatory power. Based on previous studies, too long or too short CCC suggests that the working capital levels have less than optimal effect on profitability. CCC is seen as a proxy for WCM and is the liquidity ratio that captures the timing of money and lines up best with the theory of value maximization, why we choose to test the ratio as input in the models. A longer CCC ties up more cash compared to a shorter CCC and could be seen as inefficient WCM. Thus, CCC could help predict poor WCD.

$$\text{orders} = \frac{(\text{Orders}_{t-2} - \text{Orders}_{t-3})}{(\text{net WC}_t - \text{net WC}_{t-1})} \tag{7}$$

where

$$\Delta(\text{net WC})_t = \Delta(\text{Net working capital}_t) = (\text{net WC}_t - \text{net WC}_{t-1})$$

$$= \Delta(\text{Operating current assets – Operating current liabilities}) \text{ at time t}$$

$$\text{poorWCDfreq} = \text{Poor WCD frequency} = \frac{\text{Sum of poor classifications for entity}_i \text{ till } t-1}{\text{Entity}_i\text{'s length of life in quarters until } t-1} \quad (8)$$

$$\text{CCC} = \text{Cash Conversion Cycle} = \text{DSO} + \text{DIO} - \text{DPO} \quad (9)$$

where

$$\text{DSO} = \text{Days Sales Outstanding} = \frac{(\text{Accounts receivables}_t + \text{Accounts receivables}_{t-1})/2}{\text{Revenues}/365}$$

$$\text{DIO} = \text{Days in Inventory Outstanding} = \frac{(\text{Inventory}_t + \text{Inventory}_{t-1})/2}{\text{Cost of goods sold}/365}$$

$$\text{DPO} = \text{Days Payable Outstanding} = \frac{(\text{Accounts payables}_t + \text{Accounts payables}_{t-1})/2}{(\Delta\text{Inventory}_t + \text{Cost of goods sold})/365}$$

6.1.1 Outliers

To get an overview of our data and find outliers, we used box whiskers diagrams (boxplots). The difference between the upper and lower quartile is called interquartile range (IQR). A typical approach to define outliers is (Upton, 1996);

$$\text{Values} > \text{Q3} + 1.5 \times \text{IQR}$$

$$\text{Values} < \text{Q1} - 1.5 \times \text{IQR}$$

To reduce the impact of outliers we have chosen to winsorize the values to a maximum of $\text{Q3} + 1.5 \times \text{IQR}$ and to a minimum of $\text{Q1} - 1.5 \times \text{IQR}$. For the entire data set, 8.61% of the values have been winsorized, which is similar to for example Dewaelheyns & van Hulle's (2006) study who winsorized the variables at 5% and 95%, i.e. in total 10% of the values. When separating CCs and PCs, 9.26% and 8.81% of the values were winsorized respectively. The allowed range of each key ratio is shown in table 6.2.

Table 6.2
The allowed range for the initial selection of key ratios

	All entities		CC entities		PC entities	
Variables	min	max	min	max	min	max
ROA	-0.164	0.314	-0.156	0.300	-0.188	0.359
ROE	-0.738	1.540	-0.658	1.407	-0.929	1.858
rd	0.000	0.024	-0.013	0.025	-0.011	0.022
tax	-0.480	0.801	-0.487	0.811	-0.461	0.769
assetturn	-1.059	3.252	-1.172	3.581	-0.717	2.374
invint	-0.344	0.809	-0.311	0.703	-0.392	1.107
cashpos	-0.783	1.384	-0.738	1.361	-0.830	1.403
shortliq	-0.390	3.849	-0.172	3.583	-1.281	5.038
assetstruct	-0.255	0.570	-0.163	0.391	-0.328	0.869
assetliq	-0.282	1.053	-0.240	0.903	-0.097	1.197
finstruct	-0.217	1.016	-0.200	0.957	-0.238	1.116
businessg	-0.502	0.533	-0.522	0.564	-0.451	0.456
geq	-0.318	0.399	-0.353	0.412	-0.271	0.408
gdebt	-0.560	0.505	-0.601	0.563	-0.479	0.395
size	7.986	15.457	7.986	14.900	9.728	15.457
CCC	-141.908	169.758	-204.579	201.916	-59.158	128.685
orders	-9.583	10.510	-9.482	10.369	-9.900	10.858
poorWCDfreq	0.000	0.532	0.000	0.538	0.000	0.598

6.2 Choice of prediction model

To decide what statistical method to use when predicting poor WCD we have evaluated the methods used in previous studies predicting bankruptcy. Multivariate models (allowing several variables to together predict poor WCD) are preferred over univariate models (one single variable predicts poor WCD) as prediction power generally becomes higher (Skogsvik, 1988a). Among the multivariate models used in these studies, multivariate discriminant analysis (MDA) has been common (e.g. Altman, 1968; Altman, 1971; Deakin, 1972; Edmister ,1972; Blum, 1974; Elam, 1975; Sinkey Jr, 1975; Altman & Loris 1976; Altman, Haldeman & Naraya, 1977; Moyer, 1977; Norton & Smith, 1979; Dambolena & Khoury, 1980; Ohlson, 1980). However, we have chosen not to use MDA in order to avoid the problems related to the statistical requirements on the distributional properties of the independent variables when using this method. Firstly, the independent variables (i.e. our key ratios) need to follow a normal distribution and secondly the variance-covaraince matrices for the independent variables need to be the same for the two categories of poor and non-poor entities (Ohlson, 1980), which generally does not hold for financial ratios (Foster, 1986; Skogsvik 1988a). Also, MDA does not provide estimated probabilities of an event (Ohlson, 1980; Skogsvik & Skogsvik, 2013), which for us is a desirable outcome.

Our dependent variable is binary with the two different categories; poor or non-poor. Logit/probit analysis was used already in relatively early attempts to predict bankruptcy (e.g. Ohlson, 1980; Skogsvik, 1988a) but is still the predominant statistical method used to estimate models for binary outcomes (Magnac, 2006), even though we have seen an extensive development of alternative models during the last decades (Horowitz & Savin, 2001). Logit/probit analysis does not require the assumptions of MDA and the outcome can easily be translated into probabilities (Ohlson, 1980). The logit/probit analysis relies on the existence of an unobservable index (V) for poor WCD in our case, which is assumed to be a linear function of some independent variables (AR_i):

$$V = \delta_0 + \delta_1 AR_1 + \delta_2 AR_2 + \ldots + \delta_I AR_I \quad (10)$$

where

V= index of poor WCD t-1

AR_i = accounting ratio i t-1

δ_i = coefficient of accounting ratio i t-1

(Skogsvik, 1990)

For every observation it is assumed to exist a critical index value $\overline{V}$; so that $V \leq \overline{V}$ for non-poor entities and $V > \overline{V}$ for poor entities (Skogsvik, 1990). The difference between probit and logit analysis is that $\overline{V}$ is assumed to be normally distributed in probit while in logit it is assumed to follow a logistic function. The dependent variable assumes the value 1 if the entity is poor and 0 if non-poor. In a probit/logit analysis, the probability for non-poor can be written as:

$$p(\text{poor WCD} = 0|V) = p(V \leq \overline{V})$$

The probability for poor can then be written as:

$$p(\text{poor WCD} = 1|V) = 1 - p(V \leq \overline{V})$$

(Skogsvik, 1988a)

The results using logit and probit analysis almost always converge when looking at the probabilities generated by the models (Skogsvik, 1988a; Long & Freeze 2003). We have chosen to use logit analysis in our study due to no specific reason other than that the transformation from the value V into probability is somewhat easier using logit than probit. Logit was first developed from probit analysis by Berkson (1944) and was later developed and became more sophisticated through the work of among others McFadden (2001) and Train (2003). Let $\hat{p}$ indicate an entity's estimated probability of becoming poor. When using logit analysis this probability can be written as:

$$\ln\left(\frac{\hat{p}}{1-\hat{p}}\right) = V \tag{11}$$

And $\hat{p}$, can then be calculated as:

$$\hat{p} = \frac{1}{1+e^{-V}} \tag{12}$$

(Norton & Wang, 2004)

The coefficients $(\delta_0, \delta_1, \delta_2 \ldots \delta_I)$ in function (10) have been estimated using a maximum likelihood method (see Appendix 3 for more information) in the statistical program STATA.

6.3 Finding the final combination of key ratios in the prediction models

The significance of coefficients can be evaluated using t-test, and the goodness of fit of estimated models can be evaluated using a likelihood ratio index proposed by McFadden (1972) (Ohlson, 1980, Skogsvik, 1988a). McFadden's (1972) likelihood ratio index compares a model using all the explanatory variables to a model with no variables (Hu, Shaou & Palta, 2006). A higher likelihood ratio index indicates a better goodness of fit but should only be used to compare models predicting the same event using the same set of data, and not as a comparison to other prediction models (Long & Freese, 2006).

A first step to find a satisfying combination of ratios was to exclude all ratios with coefficients not significant at a 10% level. To further find the combination of ratios that would give a high predictability but still contain a limited number of ratios we, like Dewaelheyns & van Hulle (2006), used the stepwise forward and backward function, an estimation technique that allows us to reduce the number of variables while preserving the likelihood ratio at a level close to the model containing all ratios. We are aware of the limitations of using a stepwise forward and backward modeling in a statistical package like STATA to limit the variables included in the final model. Selection bias will occur as the orders of the variables included or excluded affects the selected model (Derksen & Keselman, 1992). The choice of using stepwise may have resulted in a final model that is not ultimate in terms of prediction power. However, we do not aim to find the ultimate model but rather a model with a satisfying prediction power containing a limited number of variables that enables easy and practical application of the model. The result is not used to evaluate predictability of the model itself or for comparison with other prediction models but is solely an approach to limit the number of variables. After every stepwise we exclude the least explanatory variable to each model if the reduction of the variable did not reduce the likelihood ratio significantly.

The prediction power of the final model is evaluated based on the percentage mean errors made by the model (see the section *Evaluation of the model*). To further ensure that the models do not lose prediction power when excluding an explanatory variable suggested by the stepwise function, we also test if the area under the ROC curve (receiver operating characteristics) is significantly reduced by the exclusion. This is a common approach to compare prediction powers across models and the differences can be chi-squared tested (Chava & Jarrow, 2004).

6.4 Evaluation of the models

6.4.1 Mean error

In line with bankruptcy prediction model studies, we look at misclassifications made by the models to evaluate its prediction powers. The prediction powers can be tested by applying the models on the sample to see with what probability the entities are estimated to be poor the coming quarter. To be able to classify an entity as poor or non-poor, a cutoff point p needs to be determined such that entities with $\hat{p} > p$ are classified as poor and $\hat{p} < p$ as non-poor. The model can make two types of errors:

Type I errors: poor entities are classified as non-poor as $\hat{p} < p$

Type II errors: non-poor entities are classified as poor as $\hat{p} > p$

The choice of cutoff point, p, involves a trade-off between the size of type I and type II errors (Skogsvik & Skogsvik, 2013).The higher the cutoff point, the more type I errors are made as an entity needs a relatively high probability of becoming poor in order to be classified as poor, on the other hand the higher the cutoff point the fewer type II errors. Likewise, the lower cutoff point the less type I errors and the more type II errors are made. A common approach in bankruptcy studies has been to choose the cutoff point that minimizes the mean error (Ohlson, 1980; Skogsvik, 1988a).

The three different approaches used to calculate the mean error are:

$$f(1) = \left[\frac{\mathrm{N(type\ I\ errors)}}{\mathrm{N(poor\ entities)}} + \frac{\mathrm{N(type\ II\ errors)}}{\mathrm{N(non-poor\ entities)}}\right] \times 0.5 \tag{13}$$

$$f(2) = y \times \left[\frac{N(\text{type I errors})}{N(\text{poor entities})}\right] + (1 - y) \times \left[\frac{N(\text{type II errors})}{N(\text{non} - \text{poor entities})}\right] \quad (14)$$

$$f(3) = z \times \left[\frac{N(\text{type I errors})}{N(\text{poor entities})}\right] + (1 - z) \times \left[\frac{N(\text{type II errors})}{N(\text{non} - \text{poor entities})}\right] \quad (15)$$

where

N(type I errors) = the number of type I errors

N(type II errors) = the number of type II errors

N(poor entities) = the number of poor entities in the sample

N(non-poor entities) = the number of non-poor entities in the sample

y = the proportion poor entities in the population

z = the proportion poor entities in the sample
(Skogsvik & Skogsvik, 2013)

As the proportions of poor and non-poor entities have historically been stable in the sample (see table 1 and 2), z can be assumed to be equal to y and thus f(2)=f(3), why only f(2) will be used.

If assuming the key ratios are randomly distributed among poor and non-poor entities, f(1) will on average be 50% independent of cutoff point (Skogsvik, 1988b). If knowing the a priori probability of failure, f(2) can be compared to two naive approaches of classifying the entities without using a model:

a) All entities are classified in accordance with the category that has a priori highest probability of occurring
b) Entities are randomly classified proportionate to the a priori probability of respective category

(Skogsvik, 1988a)

Using approach a), all entities are predicted to be non-poor, resulting in 100% type I errors and 0% type II errors. The mean error would then on average be: 0.2583×100% + 0.7417×0% = 25.83%. Approach b) predicts 25.83% as poor and 74.17% as non-poor, resulting in 19.16% (0.2583×74.17%) type I errors and 19.16% (0.7417×25.83%) type II errors and thus the mean error made on average is 0.2583×19.16% +

0.7417×19.16% = 38.32%. Approach b) results in a prediction power of 61.68% (1-38.32%). The model's prediction power is preferably assessed using f(2) as it takes into account the a priori proportion of poor an non-poor entities. f(1) will still be calculated as it can be compared to the prediction power in previous bankruptcy studies. Table 6.3 summarizes the mean errors and the respective prediction powers from the naive approaches that will be used for comparisons with the respective models' prediction power when using mean error f(2).

Table 6,3

Mean error f(2) and respective prediction power(2) for the two naive approaches a) and b)

	All Entities		CC Entities		PC Entities	
	f(2)	prediction power(2)	f(2)	prediction power(2)	f(2)	prediction power(2)
Approach a)	0.2583	0.7417	0.2535	0.7465	0.2705	0.7295
Approach b)	0.3832	0.6168	0.3785	0.6215	0.3947	0.6053

6.4.2 The average error cost

The approach of minimizing the mean error has however been criticized already by Beaver (1966), as it does not incorporate the probable difference in cost of a type I and type II errors respectively (Skogsvik, 1988a). The approach is only appropriate if the cost of type I errors equal that of type II errors (ibid). When costs of the two types differ, the average error cost could be used to evaluate the model's prediction power instead of the minimized mean error. The average error cost is calculated as:

$$\overline{\mathrm{cost}} = \mathrm{y} \times \left[\frac{\mathrm{N(type\ I\ erros)}}{\mathrm{N(poor\ entities)}}\right] \times \mathrm{cost_I} + (1-\mathrm{y}) \times \left[\frac{\mathrm{N(type\ II\ errors)}}{\mathrm{N(non-poor\ entities)}}\right] \times \mathrm{cost_{II}} \qquad (16)$$

Where $\mathrm{cost_I}$ is the cost associated with a type I error and $\mathrm{cost_{II}}$ with a type II error.

(Skogsvik & Skogsvik, 2013)

The probability cutoff point,p, to use can be derived based on the trade-off between expected error costs, calculated as:

Expected error cost of type I errors: $\mathrm{p} * \mathrm{cost_I}$

Expected error cost of type II errors: $(1-\mathrm{p}) * \mathrm{cost_{II}}$

An entity is classified as poor when $\mathrm{p} * \mathrm{cost_I} > (1-\mathrm{p}) * \mathrm{cost_{II}}$

This decision rule implies a probability cutoff point, p, equal to:

$$p = \frac{1}{\left(1 - \frac{\mathrm{cost_I}}{\mathrm{cost_{II}}}\right)} \tag{17}$$

(ibid)

The average error cost will be used in the analysis to evaluate the models' prediction power when it can be assumed to exist a difference between $\mathrm{cost_I}$ and $\mathrm{cost_{II}}$.

6.5 Testing the validation and robustness of the prediction powers

Testing the prediction power using the sample data will yield fewer errors than if the models are tested on new data (Ohlson, 1980). Still, we will use the entire sample when estimating our models to ensure best prediction power (ibid). To test the validation of our results, time series validation will be performed, something that is encouraged by Joy & Tollefson (1975). Time series validation means the model is re-estimated using part of the data in our sample and the re-estimated model is tested on later data not used to estimate the model (see table 6.4). The final combination of key ratios is kept while the coefficients are re-estimated. A ROC curve for each time series validation test is performed to evaluate the differences between the in- and out-of-sample tests, where the differences in area under the ROC curves are chi-squared tested to assess the results' significance (Chava & Jarrow, 2004). Besides testing the models' prediction power, time series validation will be useful to assess how many years of data is needed to estimate the models and how long the models are valid before re-estimation is necessary.

Table 6,4

Time series validation periods and their respective testing periods

Estimation period	Testing period	Estimation period	Testing period
2010	2011	2010-2012	2013
2011	2012	2010	2012
2012	2013	2010	2013
2010-2011	2012	2011	2013
2011-2012	2013	2010-2011	2013

7. Results and analysis

The section below covers our results and analysis. Firstly, we show and analyze the results using all data (both CCs and PCs), what we call the original model, secondly we present two separate models based on the activity CC and PC and discuss their differences.

7.1 Results for the original model (estimated using both CC and PC entities)

Table 7.1

Original model

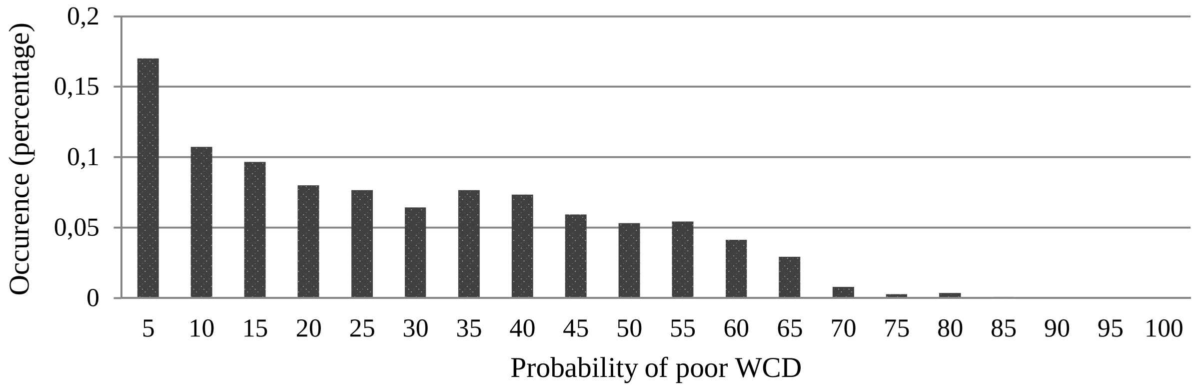
Variables	Coefficients	*t*-Statistics
assetturn	-1.226	0.000
invint	-3.438	0.000
assetstruct	-4.303	0.000
assetliq	4.237	0.000
poorWCDfreq	-16.705	0.000
geq	-0.652	0.006
cons.	6.048	0.000

f(1) = 0.2634, prediction power(1) = 0.7366
f(2) = 0.2079, prediction power(2) = 0.7921

The original model results in a final combination of six key ratios (assetturn, invint, assetstruct, assetliq, poorWCDfreq and geq) that are statistically significant on a 1% significance level or lower (see table 7.1). The ratios with a negative coefficient decrease an entity's probability of becoming poor and increase when a positive coefficient. When minimizing the mean error f(2), the original model has a prediction power(2) of 79.21% which can be compared to on average 61.68% correctly classified entities using the naive approach b) or 74.17% if using approach a). Using f(1), the mean error to use for comparisons with bankruptcy studies, results in a prediction power(1) of 73.66%. f(2) is minimized at the cutoff point 48.60% and f(1) at 27.05%.

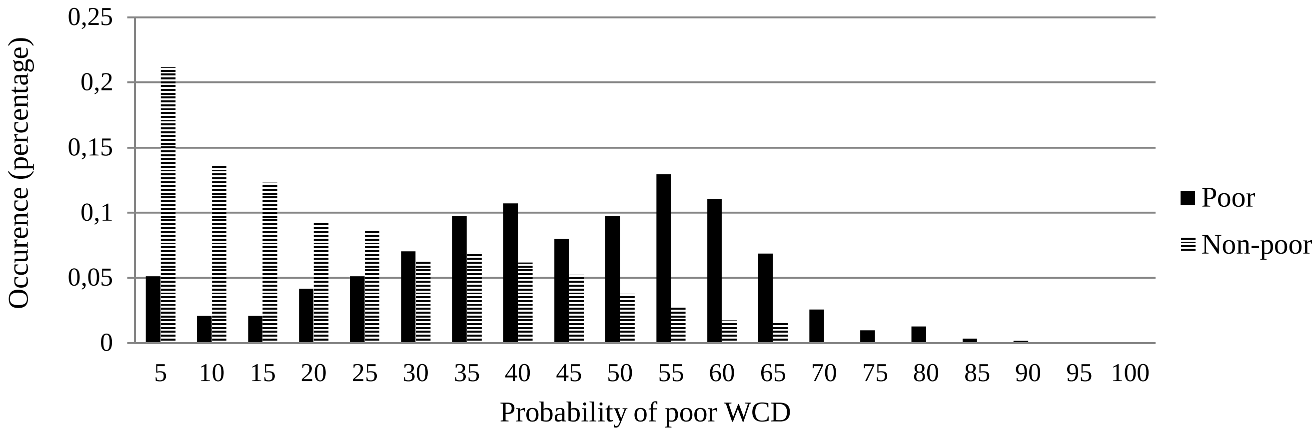
Graph 7.1

Estimated probabilities for all entities using the original model (both poor and non-poor entities)



Graph 7.2

Estimated probabilities for poor and non-poor entities respectively using the original model



Graph 7.1 illustrates the entire sample's probabilities. Most entities have low probabilities (from 0-5%) and a very small number of observations reach probabilities between 70-100%. Graph 7.2 illustrates that poor entities on average have higher probabilities than non-poor, indicating that the model manages to some extent to classify entities as poor or non-poor correctly. Most non-poor entities are distributed among the low probabilities while the number of poor entities peak at a probability of 55%. The mean probability for non-poor entities is 20.54% while for poor entities it is higher, 41.01%. Graph 7.2 is useful in assessing the effect of a given cutoff point. Through graph 7.1 one can see how many entities in the sample that we classify as poor by having a certain cutoff point and graph 7.2 can further be used to evaluate the misclassifications made i.e. type I (classifying poor entities as non-poor) and type II (classifying non-poor entities as poor) errors for a certain cutoff point.

7.2 Analysis – original model's prediction power

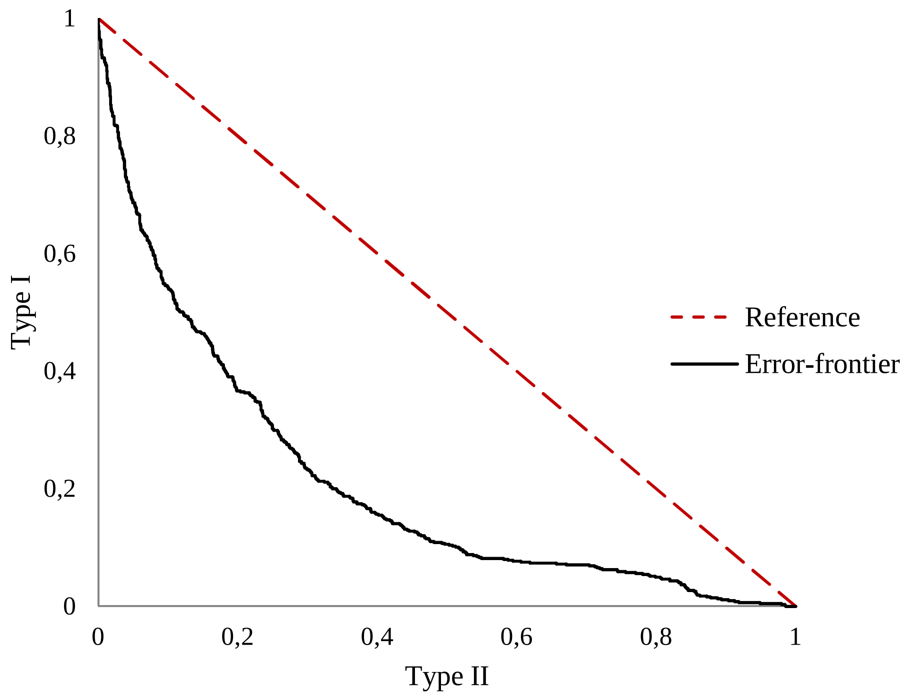
7.2.1 The original model's prediction power

Our model makes a mean error f(1) of 26.34% which is lower than 50%, the implied mean error if the key ratios are randomly distributed among poor and non-poor entities. Our model's prediction power(1) is somewhat lower compared to models predicting bankruptcy, where for example Skogsvik's (1988a) model predicting bankruptcy one year ahead resulted in a prediction power(1) of 83.30% and Ohlson's (1980) at 85.00% one year prior to bankruptcy. This is in line with what we expected as poor WCD was anticipated to cause a less clear deterioration in key ratios one quarter prior to the event than what can be seen in the ratios one year prior to bankruptcy. Our model's prediction power(1) is at about the same level as Skogsvik's (1988a) model predicting bankruptcy six years ahead, illustrating the long deterioration process of financial variables several years prior to bankruptcy, which is not the case for poor WCD. Thus, predicting poor WCD two quarters ahead or more, the prediction power will most likely be low, as already expected and discussed.

As mentioned, we view the mean error calculated according to f(2) as more realistic as it takes into account the a priori proportions of poor and non-poor entities. To evaluate the model's prediction power(2), we compare it to a situation where classification is done without a model, either according to approach a) or b). When using approach a) all entities are classified as non-poor, resulting in on average 74.17% correctly classified entities (mean error f(2) of 25.83%). Even though approach a) probably is most commonly used among companies, the approach can be viewed as optimistic if it exists poor entities. Therefore, we think that a more accurate comparison to our model would be approach b) where the company at least tries to classify some entities as poor and does so by classifying 25.83% as poor and 74.17% as non-poor, based on the proportions of the population. This would result in on average 61.68% (mean error f(2) of 38.32%) correctly classified entities. The classification with a model results in on average a mean error f(2) of 20.79% , 17.53 percentage points (pp) lower than when using approach b). It is however apparent that approach a) yields a lower mean error than approach b), the classification with the model still provides a lower mean error but the difference is reduced to 5.04 pp. Even though our model results in a lower mean error f(2) than using any of the naive approaches, further investigation of both our model's prediction power and why approach a) is better than b) for the company in terms of correctly classified entities is needed. Hence, using no model at all, the company can reach relatively close results compared to using our model. To understand this phenomenon and our model's prediction power, the mean error's components, i.e. type I and type II errors, need closer examination.

Graph 7.3

The error-frontier using the original model



Graph 7.3 illustrates the error-frontier implied by the model and demonstrates the trade-off between type I and type II errors; the more type I errors made the fewer type II errors and vice versa. The graph also visualizes the model's prediction power. The reference line shows how the mean error-frontier would look like if the model randomly assigned probabilities to entities and had no predictive ability (Chava & Jarrow, 2004). The smaller the area is between the axes and the error-frontier, the fewer misclassifications and accordingly higher prediction power. The distribution of errors depends on the choice of cutoff point, which is shown in table 7.2 and visualized in graph 7.4.

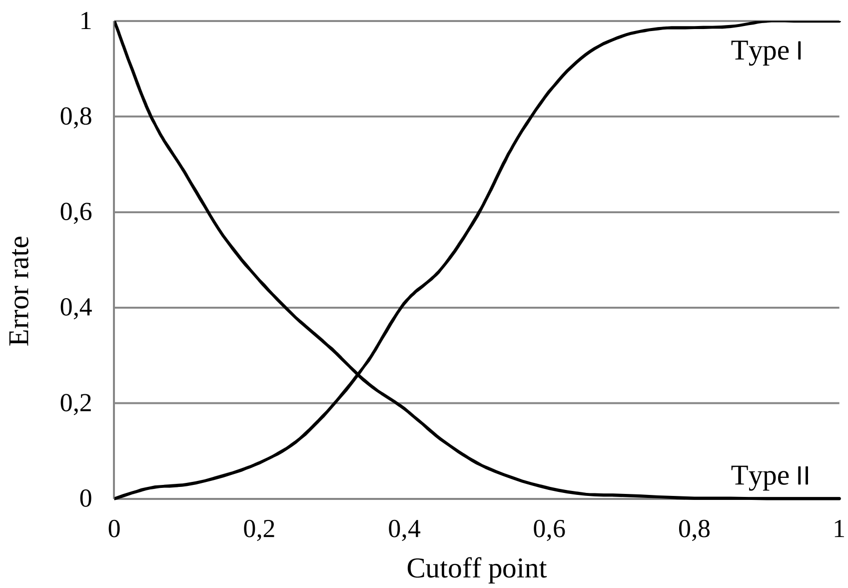
Table 7.2

Type I and type II errors for selected cutoff points with original model

Cutoff	Type I	Type II	f(2)	f(1)
0.00	0.000	1.000	0.742	0.500
0.05	0.051	0.788	0.598	0.420
0.10	0.072	0.651	0.501	0.361
0.15	0.093	0.528	0.415	0.310
0.20	0.134	0.434	0.357	0.284
0.25	0.186	0.348	0.306	0.267
0.30	0.256	0.286	0.278	0.271
0.35	0.354	0.216	0.252	0.285
0.40	0.461	0.154	0.233	0.308
0.45	0.541	0.102	0.215	0.321
0.50	0.638	0.064	0.212	0.351
0.55	0.768	0.036	0.225	0.402
0.60	0.878	0.018	0.241	0.448
0.65	0.947	0.003	0.247	0.475
0.70	0.973	0.001	0.252	0.487
0.80	0.994	0.000	0.257	0.497
1.00	1.000	0.000	0.258	0.500

Graph 7.4

Original model: type I and type II errors for given levels of cutoff points



Graph 7.4 shows the higher the cutoff point, the fewer type II errors and the more type I errors. At a cutoff point over 60.00%, the company makes almost 0% type II errors and 100% type I errors. At the intercept in graph 7.4, the cutoff point is 31.47%, resulting in a 26.87% type I and type II error rate. Type I and type II errors for a given cutoff point is shown in table 7.2. So far our approach to demonstrate prediction power has been, just like in the bankruptcy studies, to choose the cutoff point that minimizes the mean error. Lowest mean error f(2) is given at a cutoff point of 48.60% resulting in 59.68% type I errors and 7.24% type II errors. Low cutoff points give worse prediction power (2), which is explained by the large amount of type II errors that is made as more entities with lower probabilities of becoming poor will be classified as poor. When using f(1) calculation for the mean error, the mean error is minimized at a cutoff point of 27.00%, resulting in a type I error rate of 20.64% and type II error rate of 32.03%.

As the table 7.2 shows, the cutoff point chosen affects the prediction power of the model as well as the proportions of type I and type II errors. As the a priori probability of being poor (25.83%) is smaller compared to non-poor(74.17%), an approach that minimizes mean error f(2) will imply a large proportion of type I errors as poor entities are weighted lower and thus the misclassification of them has a lower effect on mean error. Type I errors are weighted lower, which also explains why approach a) results in a smaller mean error than approach b). Approach a) has only type I errors while approach b) has a relatively large proportion of type II errors. Even if our model significantly decreases type I errors, at the expense of only a slightly higher type II error rate, the high proportion given to type II errors contributes to the relatively small change in terms of mean error between our model and approach a), as this approach always make 100% type II errors and thus highly contributes to a lower mean error. Though, if there is a preference for avoiding one type of errors, the model should rather be evaluated based on its ability to avoid that certain type of errors rather than on how low mean error that can be achieved. The cutoff point should then rather be selected so that the model avoids the error that is least preferred.

7.2.2 The cost of type 1 and type 2 errors

As the model aims at predicting poor WCD, it would be preferable if poor entities were not misclassified. Theory points out the costs of having poor WCD both in terms of liquidity and profitability, and thus lower firm value, which suggests that type I errors are more costly than type II errors. Hence, the underlying reason for the need of this kind of prediction model.

Classification without a model according to approach a) has a lower mean error f(2) than b), however the former approach results in 100% type I errors and 0% type II errors, while the latter in 74.17% type I and 25.83% type II errors each. When type I errors should be avoided the company does better in classifying according to approach b) than approach a) as this results in fewer type I errors, despite a higher mean error. The minimized mean error is not appropriate for evaluating the usefulness of the model if there is a preference for avoiding type I errors.

Thus, type I errors should be reduced, but if the cutoff point is chosen so that these errors are eliminated, type II errors will be almost 100% (see table 7.2), and our model will not be very helpful as almost all entities will be classified as poor. Hence, a large proportion of the entities would be incorrectly classified which may create more costs to the company despite the fact that type I error costs ($\mathrm{cost_I}$) are higher than type II error costs ($\mathrm{cost_{II}}$). How larger $\mathrm{cost_I}$ is compared to $\mathrm{cost_{II}}$, should rather be used in order to decide on an appropriate cutoff point, and hence, would capture the usefulness of the model better in terms of cost savings compared to minimization of mean error. Table 7.3 illustrates the usefulness of our model compared to using no model at all, for different proportions of when $\mathrm{cost_I}$ is higher than $\mathrm{cost_{II}}$.

Table 7.3

Average error cost for original model compared to approach a) and approach b)

$\mathrm{cost_I}/\mathrm{cost_{II}}$	1	2	3	4	5	10	15	20
Cutoff point	0.500	0.333	0.250	0.200	0.167	0.091	0.063	0.048
Approach a) type I rate	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Approach a) type II rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Approach b) type I rate	0.742	0.742	0.742	0.742	0.742	0.742	0.742	0.742
Approach b) type II rate	0.258	0.258	0.258	0.258	0.258	0.258	0.258	0.258
Original model type I rate	0.638	0.301	0.186	0.134	0.106	0.070	0.059	0.051
Original model type II rate	0.064	0.247	0.348	0.434	0.497	0.681	0.760	0.798
Approach a) $\overline{\mathrm{cost}}$	0.258	0.517	0.775	1.033	1.292	2.583	3.875	5.166
Approach b) $\overline{\mathrm{cost}}$	0.383	0.575	0.766	0.958	1.149	2.107	3.065	4.023
Original model $\overline{\mathrm{cost}}$	0.212	0.339	0.402	0.461	0.505	0.687	0.793	0.857
Approach a) $\overline{\mathrm{cost}}$ / Original model $\overline{\mathrm{cost}}$	1.216	1.525	1.927	2.242	2.556	3.759	4.886	6.031
Approach b) $\overline{\mathrm{cost}}$ / Original model $\overline{\mathrm{cost}}$	1.804	1.696	1.906	2.079	2.275	3.067	3.866	4.697

If $\mathrm{cost_I} = \mathrm{cost_{II}}$, the cutoff point is 50.00% and thus results in a large proportion of type I errors but few type II errors. The higher $\mathrm{cost_I}$ in relation to $\mathrm{cost_{II}}$, the lower the cutoff point and the fewer type I errors. This however comes at the expense of an increased proportion of type II errors. Our model is more useful in terms of a lower average cost error rate ($\overline{\mathrm{cost}}$) compared to both approach a) and b). Table 7.3 illustrates that approach b) is better than approach a) first when $\mathrm{cost_I}$ is 3x larger or more than $\mathrm{cost_{II}}$. The explanation is that approach a) results in 0% type II errors, and although approach b) implies fewer type I errors than approach a), it still results in type II errors. The benefit of reducing type I errors exceeds the cost of the increase in type II errors first when the $\mathrm{cost_I}/\mathrm{cost_{II}}$ relation is larger than 3.

Classifying the entities using our model results in a lower $\overline{\mathrm{cost}}$ than both approach a) and b) when $\mathrm{cost}_{\mathrm{I}}$ is equal to $\mathrm{cost}_{\mathrm{II}}$, and the higher $\mathrm{cost}_{\mathrm{I}}/\mathrm{cost}_{\mathrm{II}}$ relation, the better usefulness in terms of cost savings. When $\mathrm{cost}_{\mathrm{I}}$ is 4x $\mathrm{cost}_{\mathrm{II}}$, the $\overline{\mathrm{cost}}$ is half of what it is when using both approach a) and b). Thus, prediction power using minimization of mean error indicated our model is only slightly better than approach b), taking costs of the two types of errors into account, demonstrates a significant improvement in power.

7.3 Results for separate models; CC and PC

Table 7.4

The separate models

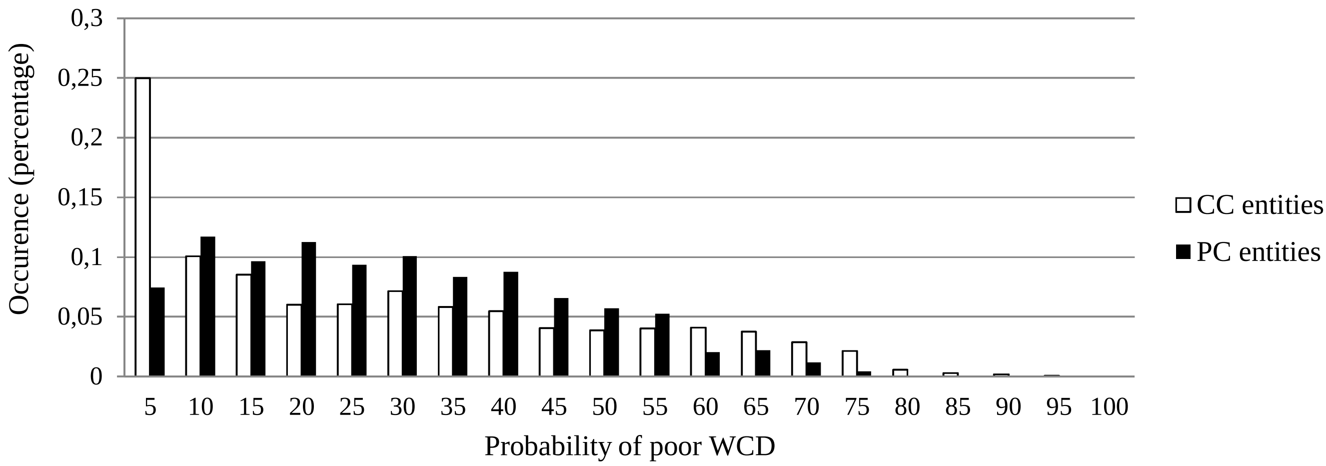
CC model			PC model		
Variables	Coefficients	*t*-Statistics	Variables	Coefficients	*t*-Statistics
assetturn	-1.114	0.000	assetturn	-1.836	0.000
invint	-3.698	0.000	invint	-2.956	0.000
assetstruct	-2.773	0.006	assetstruct	-6.293	0.000
assetliq	2.566	0.000	assetliq	6.175	0.000
poorWCDfreq	-28.077	0.000	gdebt	-1.262	0.001
cons.	9.928	0.000	poorWCDfreq	-8.704	0.000
			cons.	3.306	0.000
f(1) = 0.2370, prediction power(1) = 0.7630			f(1) = 0.3065, prediction power(1) = 0.6935		
f(2) = 0.1890, prediction power(2) =0.8110			f(2) = 0.2310, prediction power(2) =0.7690		
f*(1) = 0.2643, prediction power*(1) = 0.7357			f*(1) = 0.3245, prediction power*(1) = 0.6755		
f*(2) = 0.2051, prediction power*(2) =0.7949			f*(2) = 0.2281, prediction power*(2) =0.7719		

* Original model used on CC and PC entities respectively

The separate models include almost the same variables as the original model. However, geq is not included in any the two separate models. The only variable separating the CC model and the PC model is gdebt (table 7.4). To see if there is an improvement having two separate models rather than using the original model, we use the original model to predict poor WCD among CCs and PCs separately and compare the results to if separate models are used. The separate model for CC compared to using the original model is slightly better (f(2)>f*(2)) while slightly worse for PC (f(2)<f*(2)). f(2) is minimized at a cutoff point of 48.29% for CC and 43.83% for PC.

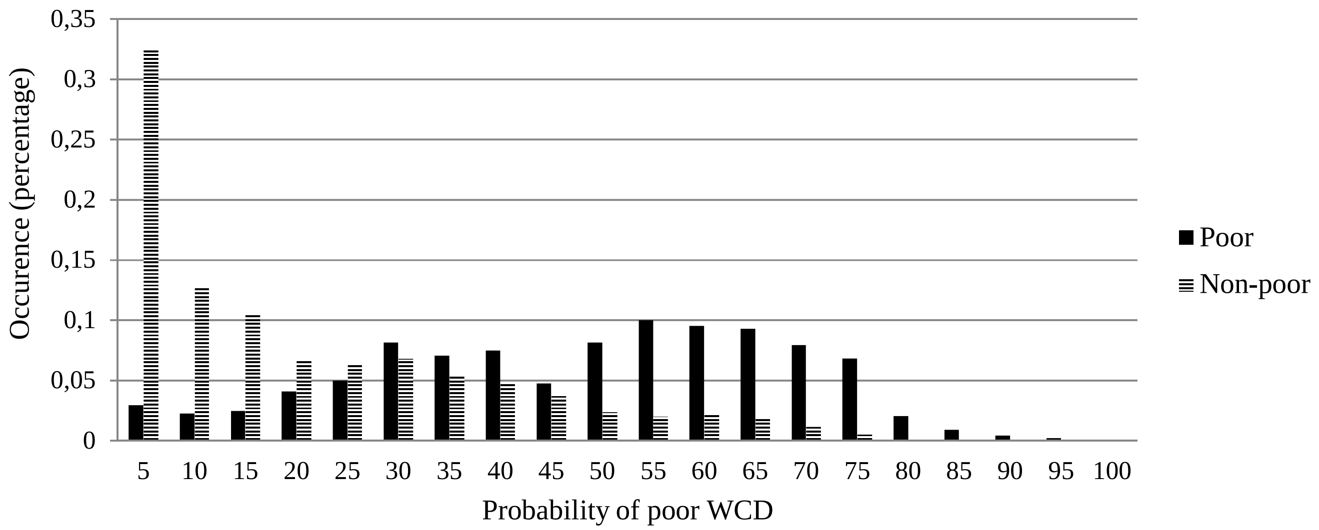
Graph 7.5

Estimated probabilities of poor WCD using the separate models for CC and PC entities



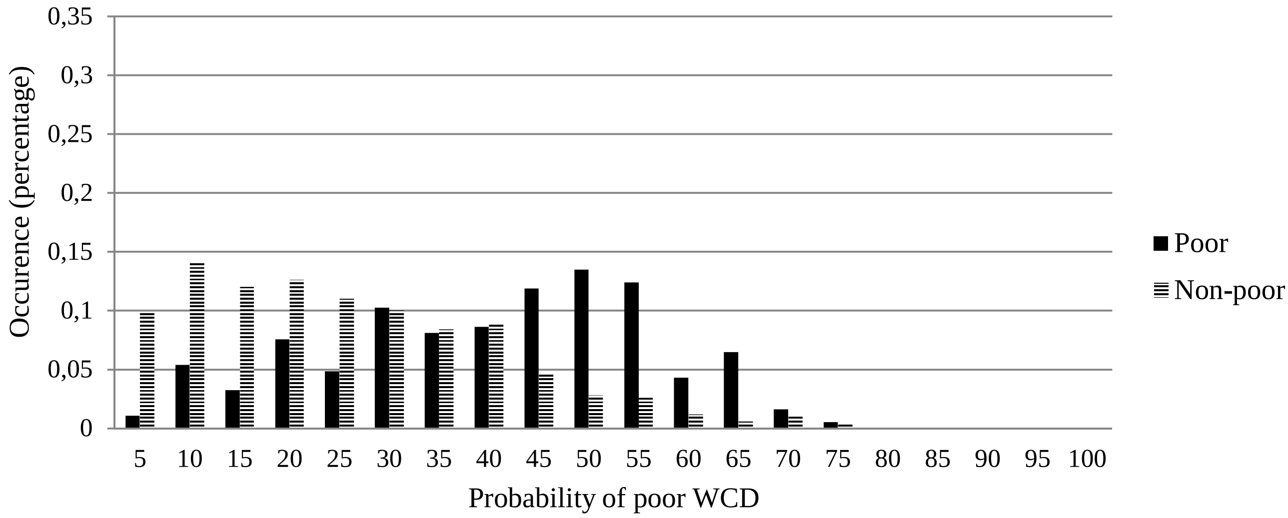
Graph 7.6

Estimated probabilities for poor and non-poor CC entities respectively using the CC model



Graph 7.7

Estimated probabilities for poor and non-poor PC entities respectively using the PC model



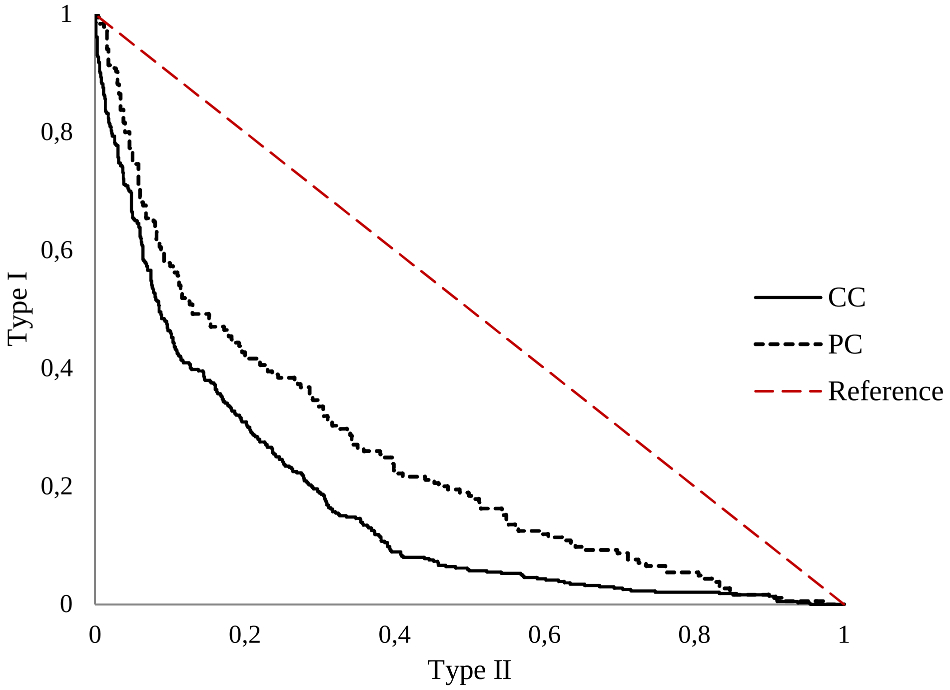
CCs seem to have on average lower probabilities of poor WCD compared to PCs, as illustrated in graph 7.5. As shown by graph 7.6 and 7.7, both the CC and PC models estimate higher probabilities for poor than for non-poor entities, which was also the case when using the original model. Most non-poor CC entities are centered on low probabilities of poor WCD and poor entities on higher probabilities, while thus the same pattern is less visible among both non-poor and poor PC entities. The mean probability for poor (non-poor) PC entities is 37.86% (23.04%) and 45.66% (18.4%) for CC entities.

7.4 Analysis - the CC and PC models' prediction powers

Following the discussion on the preference of avoiding type I errors the company will do best if using approach b) to predict poor WCD without the access to a model. Both the PC and CC models result in a lower mean error f(2) than approach b), 18.94 pp lower for CC and 16.37 pp for PC. The reduction in mean error f(2) from using a model is slightly larger for the CC model, which also is illustrated in graph 7.8 where the area between the error-frontier and the two axes is smaller for CC compared to PC.

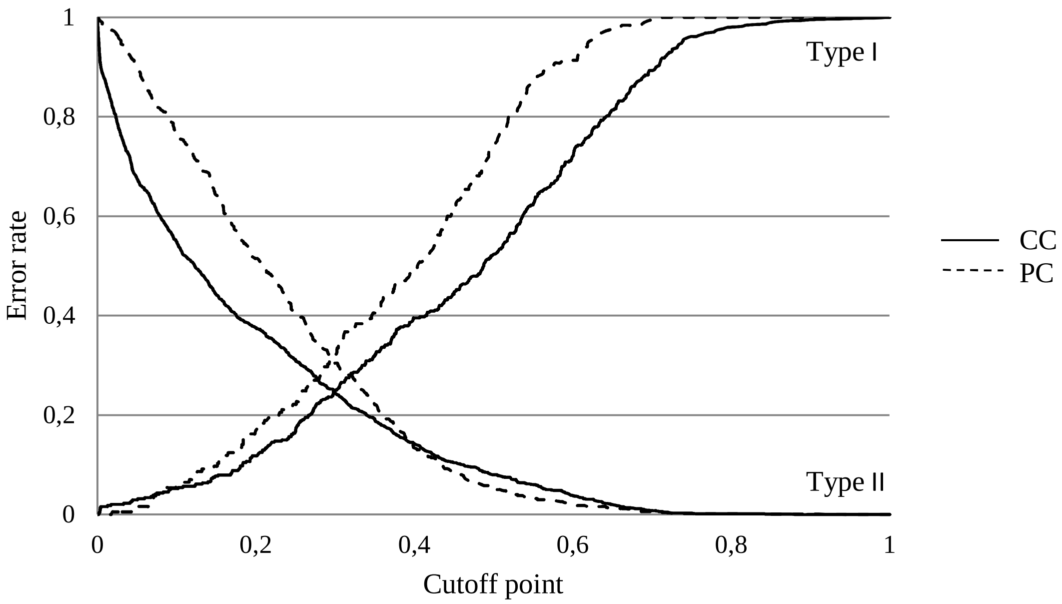
Graph 7.8

The error-frontiers using the separate models for CC and the PC



Graph 7.9

CC model and PC model: type I and type II errors for given levels of cutoff points



The cutoff point where the percentage of type I and type II errors are equal is very similar for PC and CC, as can be illustrated by graph 7.9. The cutoff point for CC and PC is 29.84% and 29.69% respectively. Note, the PC model has both a steeper type I and type II curve compared to the CC model, which is a result of both the shorter probability range and the smaller difference in probabilities for non-poor and poor PC entities (shown in graph 7.7). This indicates that more errors are plausible when predicting PC entities as poor or non-poor, a fact evident as f(2) (prediction power(2)) for the PC model is higher (lower). A lower cutoff point is required in order to minimize mean error in the PC model, which is also the case (also illustrated in table 7.5).

Table 7.5

Type I and type II errors for selected cutoff points with the separate models for CC and PC

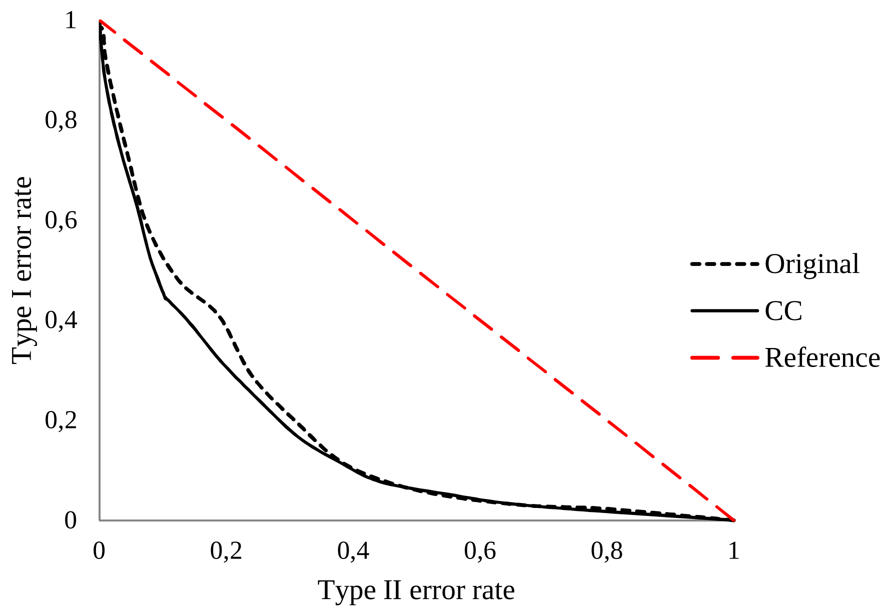
	CC				PC			
Cutoff	Type I	Type II	f(2)	f(1)	Type I	Type II	f(2)	f(1)
0.00	0.000	1.000	0.742	0.500	0.000	1.000	0.730	0.500
0.05	0.051	0.788	0.598	0.420	0.011	0.902	0.661	0.456
0.10	0.072	0.651	0.501	0.361	0.065	0.762	0.573	0.413
0.15	0.093	0.528	0.415	0.310	0.097	0.641	0.494	0.369
0.20	0.134	0.434	0.357	0.284	0.173	0.515	0.423	0.344
0.25	0.186	0.348	0.306	0.267	0.222	0.405	0.355	0.313
0.30	0.256	0.286	0.278	0.271	0.324	0.305	0.310	0.314
0.35	0.354	0.216	0.252	0.285	0.405	0.220	0.270	0.313
0.40	0.461	0.154	0.233	0.308	0.492	0.132	0.230	0.312
0.45	0.541	0.102	0.215	0.321	0.611	0.086	0.228	0.348
0.50	0.638	0.064	0.212	0.351	0.746	0.058	0.244	0.402
0.55	0.768	0.036	0.225	0.402	0.870	0.032	0.259	0.451
0.60	0.878	0.018	0.241	0.448	0.914	0.020	0.262	0.467
0.65	0.947	0.003	0.247	0.475	0.978	0.014	0.275	0.496
0.70	0.973	0.001	0.252	0.487	0.995	0.004	0.272	0.499
0.75	0.982	0.001	0.254	0.491	1.000	0.000	0.271	0.500
0.80	0.994	0.000	0.257	0.497	1.000	0.000	0.271	0.500
0.85	0.998	0.000	0.258	0.499	1.000	0.000	0.271	0.500
1.00	1.000	0.000	0.258	0.500	1.000	0.000	0.271	0.500

The cutoff point that minimizes mean error in the original model and the separate CC and PC models does not differ much, nor the respective minimum mean errors achieved by the models. However, the preference of avoiding type I errors has not been taken into account. Next section will further evaluate the prediction power of the separate models to the original model.

7.4.1 The CC and PC models' prediction powers in comparison to the original model's

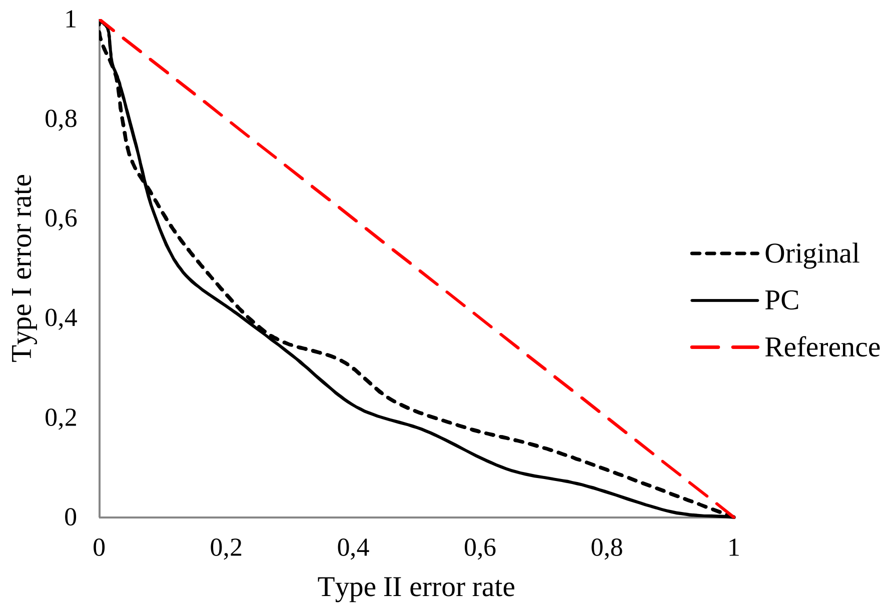
Graph 7.10

Error-frontiers for CC entities using the CC model compared to original model



Graph 7.11

Error-frontiers for PC entities using the PC model compared to original model



The difference between the two error frontiers when using the original and the separate model (shown in graph 7.10 and 7.11) is not significant for the CC or the PC model, indicating that the prediction power has not significantly improved by using separate models. Due to the differences between CCs and PCs (which is illustrated in Appendix 4, table 1, presenting differences in mean values of the initial selection of key ratios between CCs and PCs), we expected higher prediction power for the separate models compared to the original model. The separate models include about the same ratios, indicating that the ratios explanatory to predict poor WCD are similar for both PCs and CCs, even though CCs and PCs differs in terms of operating activities.

As discussed in the analysis on the prediction power of the original model, type I errors are least preferred to type II errors. Even though we did not find a significant decrease in the area under the error frontier, it the case of PCs, the separate model is better compared to the original model for low levels of type I error rates (see graph 7.11). The same can however not be seen for the CC model (see graph 7.10). To further investigate the models' usefulness when fewer type I errors are desirable, we again look at the average error costs ($\overline{cost}$) for the models.

Table 7.6

Average error cost for CC model compared to original model, approach a) and approach b)

costI/costII	1	2	3	4	5	10	15	20
Cutoff point p	0.500	0.333	0.250	0.200	0.167	0.091	0.063	0.048
Approach a)Type I rate	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Approach a) Type II rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Approach b)Type I rate	0.747	0.747	0.747	0.747	0.747	0.747	0.747	0.747
Approach b) Type II rate	0.254	0.254	0.254	0.254	0.254	0.254	0.254	0.254
CC model Type I rate	0.555	0.291	0.168	0.118	0.080	0.050	0.034	0.030
CC model Type II rate	0.075	0.210	0.312	0.376	0.415	0.570	0.650	0.683
Approach a) $\overline{cost}$	0.254	0.507	0.761	1.014	1.268	2.535	3.803	5.070
Approach b) $\overline{cost}$	0.378	0.568	0.757	0.946	1.135	2.082	3.028	3.974
CC model $\overline{cost}$	0.196	0.304	0.361	0.400	0.411	0.552	0.615	0.660
Approach a) cost / CC model $\overline{cost}$	1.290	1.667	2.109	2.533	3.086	4.589	6.187	7.687
Approach b) cost / CC model $\overline{cost}$	1.927	1.866	2.099	2.363	2.765	3.768	4.926	6.025
CC original model Type I rate	0.591	0.384	0.250	0.195	0.148	0.089	0.068	0.057
CC original model Type II rate	0.075	0.193	0.262	0.311	0.343	0.448	0.500	0.534
CC original model $\overline{cost}$	0.206	0.339	0.386	0.430	0.444	0.559	0.633	0.687
CC original model $\overline{cost}$ / CC model $\overline{cost}$	1.047	1.114	1.070	1.075	1.080	1.012	1.029	1.042

Table 7.7

Average error cost for PC model compared to Original model, approach a) and approach b)

costI/costII	1	2	3	4	5	10	15	20
Cutoff p	0.500	0.333	0.250	0.200	0.167	0.091	0.063	0.048
Approach a)Type I rate	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Approach a) Type II rate	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Approach b)Type I rate	0.730	0.730	0.730	0.730	0.730	0.730	0.730	0.730
Approach b) Type II rate	0.271	0.271	0.271	0.271	0.271	0.271	0.271	0.271
PC model Type I rate	0.746	0.384	0.222	0.173	0.124	0.054	0.016	0.011
PC model Type II rate	0.058	0.253	0.405	0.550	0.593	0.800	0.860	0.910
Approach a) $\overline{\text{cost}}$	0.271	0.541	0.812	1.082	1.353	2.705	4.058	5.410
Approach b) $\overline{\text{cost}}$	0.395	0.592	0.789	0.987	1.184	2.171	3.157	4.144
PC model $\overline{\text{cost}}$	0.244	0.392	0.475	0.589	0.601	0.730	0.693	0.722
Approach a) cost / PC model $\overline{\text{cost}}$	1.108	1.381	1.708	1.838	2.251	3.708	5.855	7.491
Approach b) cost / PC model $\overline{\text{cost}}$	1.616	1.511	1.661	1.676	1.970	2.975	4.556	5.738
PC original model Type I rate	0.719	0.568	0.449	0.395	0.378	0.324	0.254	0.238
PC original model Type II rate	0.050	0.126	0.200	0.240	0.267	0.371	0.419	0.453
PC original model $\overline{\text{cost}}$	0.231	0.399	0.510	0.602	0.706	1.148	1.336	1.617
PC original model $\overline{\text{cost}}$/PC model $\overline{\text{cost}}$	0.946	1.019	1.074	1.023	1.175	1.573	1.928	2.239

Table 7.7 confirms and strengthens what illustrated in graph 11; when a cutoff point that lowers type I errors is chosen, the PC model is preferable to the original model as the $\overline{\text{cost}}$ for the PC model is lower than for the original model. This is especially evident when cost_{I} is 5x or more than cost_{II}. The reason is because the PC model manages to make fewer type I errors compared to the original model, however, at the expense of more type II errors. Though, this trade-off is less important the higher $\text{cost}_{\text{I}}/\text{cost}_{\text{II}}$ relation. The same is not seen in the CC model; the $\overline{\text{cost}}$ for the CC model is lower than for the original model independent on $\text{cost}_{\text{I}}/\text{cost}_{\text{II}}$ relation (see table 7.6). This suggests that separate models for both CC and PC are preferred over a model including both types of activities (i.e. the original model).

When comparing the two separate models for CC and PC to the original model, it is apparent that although about the same ratios are used, the PC model differs more from the original model than in the case of the CC model in terms of both prediction power and $\overline{\text{cost}}$. This result is probably due to the large proportion of CCs (71.74%) of the total entities used to estimate the original model. Hence, the original model is probably more representative for CCs than for PCs, and thus achieves better results for CCs.

7.5 Time series validation of prediction powers

The results and analysis from the time series validation will provide answers to (1) the validation and robustness of the models' prediction powers, (2) how many years of data is needed to estimate the models and (3) how long the models are valid before re-estimation is necessary.

Table 7.8

Time series validation of area under error frontier for the original model and the separate models

		Original			CC			PC		
Estimation period	Testing period	In-sample area	Testing period area	Prob >chi2	In-sample area	Testing period area	Prob >chi2	In-sample area	Testing period area	Prob >chi2
2010	2011	0.204	0.223	0.000	0.164	0.194	0.000	0.248	0.273	0.031
2011	2012	0.204	0.205	0.859	0.164	0.176	0.002	0.248	0.267	0.058
2012	2013	0.204	0.203	0.080	0.164	0.169	0.066	0.248	0.269	0.024
2010-2011	2012	0.204	0.204	0.856	0.164	0.171	0.024	0.248	0.262	0.085
2011-2012	2013	0.204	0.203	0.509	0.164	0.165	0.561	0.248	0.264	0.060
2010-2012	2013	0.204	0.204	0.837	0.164	0.169	0.066	0.248	0.262	0.085
2010	2012	0.204	0.226	0.000	0.164	0.210	0.000	0.248	0.252	0.769
2010	2013	0.204	0.261	0.000	0.164	0.247	0.000	0.248	0.265	0.061
2011	2013	0.204	0.216	0.581	0.164	0.158	0.541	0.248	0.259	0.136
2010-2011	2013	0.204	0.206	0.589	0.164	0.173	0.001	0.248	0.259	0.033

7.5.1 The original model

Table 7.8 indicates that prediction power in terms of minimized mean error and the average error cost savings, both of which depend on the error frontier, are still valid when the original model is tested on out-of-sample data. We expected the area under the error-frontier to be underestimated as a result of the in-sample testing but no large differences of the areas are shown. When using only year 2010 to estimate the model the area is somewhat larger, indicating that this year may not be representable to predict poor WCD. The area decreases as soon as one or more years are added in the estimation period which indicates that one year is too little to estimate the model on. Two years seem to be sufficient as the area is not shown to have decreased more by including more than two years when estimating the model. With the exception of year 2010, our results are robust as no matter which years used to estimate the model, does not affect the error-frontier significantly.

As estimating the model on data using only year 2010 does not give good results, the validity of the model in the future can only be tested by looking two years ahead. The error-frontier does not significantly deteriorate two years from estimation which indicates that the model can be used at least two years without re-estimation.

7.5.2 The PC and CC model

For both CC and PC, the in-sample error-frontier is slightly higher but yet significant than almost all of the time series validated prediction results. The results indicate either that the in-sample test results in an underestimation or that using more data to estimate the model is preferable. Even though the area under the error-frontier might be underestimated and hence the prediction power and cost savings from the model overestimated, the differences between the areas are very small. Therefore, we can still conclude that using the separate models to predict poor WCD compared to both approach a) and b) is preferably in terms of fewer errors. Due to variation in results, no clear conclusion can be drawn regarding how long the separate models are expected to be valid.

7.6 Analysis – the key ratios included in the models

In a multivariate logit model, interrelation among variables is possible and thus the effect of one ratio could be difficult to evaluate as it could be dependent on the other ratios in the model. Understanding the coefficients in a statistical multivariate logit model is challenging and although arbitrary, some discussions and possible explanations to the sign of the coefficients of the key ratios in the final combinations will be provided in this section.

7.6.1 The original model

geq's coefficient is negative, meaning that the higher the geq in t-1 the lower the probability of poor WCD in t. Since no equity funding on operating entity level is made and dividends are proportionate to revenues, geq resemblances very much ROE and thus more than just growth. Profitability is related to lower levels of net working capital and better liquidity, (e.g. Shin & Soenen, 1998; Deloof, 2003; Garcia-Teruel & Martinez-Solano, 2007; Raheman & Nasr, 2007; Samiloglu & Demirgunes, 2008; Nobanee & AlHajjar, 2009; Zariyawati et al., 2009; Garcia, Martins & Brandão, 2011) and hence a high geq t-1 evidently help ensure efficient WCM, and thus decreases the likelihood of poor WCD.
Accounts receivables and inventory are a majority of an entity's current assets. On the one hand, current assets are seen as liquid assets compared to non-current assets, on the other hand they tie up cash (Burkart & Ellingsen, 2004; Eljelly, 2004). As mentioned, according to the theory of value maximization, low levels of net working capital have a positive effect on profitability and thus an entity will also have a lower risk of inadequate liquidity as less cash is tied up. The higher assetstruct the lower levels of current assets, hence accounts receivables and inventory. The ratio indicates that low levels of accounts

receivables and inventory in t-1, decreases the probability of becoming poor in t. Theory suggests that low levels of these assets are associated with higher profitability and better liquidity and thus efficient WCM. This ratio then suggests that efficient WCM in t-1 decrease the probability of poor WCD in t.

The conversion period for accounts receivables to cash is generally shorter than for inventory, and accounts receivables is therefore said to be more liquid than inventory (Burkart & Ellingsen, 2004). This is captured in the ratio assetliq**,** if it is high the entity has a high proportion of non-liquid assets, and hence inventory, among its assets, which also implies that a low proportion of the entities' assets are accounts receivables and cash and cash equivalents. Even though low levels of both accounts receivables and inventory are preferable, in the choice of the two, lower levels on inventory should be preferred due to its differences in terms of liquidity, which assetliq captures. Hence, high levels of less liquid assets and specifically inventory in t-1, increase the probability of poor WCD in t.

assetturn captures how well an entity generates revenues given its asset base. Hence, efficient management of its asset base the higher assetturn. As the asset base consists of among other working capital, the higher assetturn in t-1 illustrates efficient WCM and thus a lower probability of poor WCD in t.

A high invint suggests that the entity requires a large inventory for its revenue level. Based on theory, an entity that continually has a high invint ratio is an entity that has a higher risk of becoming poor. This is not shown in the model as the coefficient is negative. One possible explanation to the negative coefficient can be that high invint in t-1indicates excess inventory in t and thus a less probable need for inventory build-up in t. This however is not in line with what was suggested for assetturn and asstliq.

As mentioned, we expected an entity using external funds several times to finance poor WCD, would have a higher probability of becoming poor. However, high values of poorWCDfreq give a lower probability, which is further strengthened by the fact that poor entities on average have been poor fewer times than non-poor (see Appendix 2, table 1). One possible explanation is that entities that financed poor WCD in the past have realized the negative effects and thus manages to improve and thus have a less likelihood of poor WCD in t.

In summary, we can conclude that the signs of the coefficients included in the final combination are reasonable in terms of poor WCD, with the exception of invint, which is counterintuitive in terms of both theory of value maximization and empirical results.

7.6.2 The CC and PC models

Even though CCs and PCs differ in mean values of key ratios (see Appendices 4, table 1), it is apparent that similar variables apply to predict poor WCD in both CC and PC entities. geq was included in the original model but in neither of the separate models. One possible explanation is that PC entities generally are more profitable than CC entities (see Appendix 4, table 1) and therefore this measure was needed to ensure best prediction power when predicting poor WCD for CC and PC entities using the same model.

The only variable that differs between the CC and PC model is gdebt. gdebt is included in the PC model and the explanation might be that investments is an important activity in producing entities. The higher gdebt in t-1 the lower probability of becoming poor in t. A possible explanation can be that gdebt is related to investments, which normally results in higher profitability. Profitable firms are associated with low levels of net working capital and thus would indicate efficient WCM and thus lower probability of poor WCD. Also, as mentioned, PC entities are more profitable compared to CC entities.

7.6.3 Added ratios to the initial selection of key ratios

Only one out of our three added ratios to the initial selection of key ratios was included in the models, neither CCC nor orders are part of the final combinations. A long CCC does not seem to be helpful in explaining future poor WCD. This is surprising as CCC commonly have been used as a proxy for WCM in studies investigating the effect working capital has on profitability (e.g. Deloof, 2003; Eljelly, 2004; Padachi, 2006; Garcia-Teruel & Martinez-Solano, 2007; Raheman & Nasr, 2007; Samiloglu & Demirgunes, 2008; Nobanee & AlHajjar, 2009; Zariyawati et al. 2009; Gill, Biger & Mathur, 2010; Garcia, Martins & Brandão, 2011). We expected poor WCD entities to have longer CCCs than non-poor in t-1, however no significant difference of CCC for poor and non-poor entities in t-1 exists (see Appendices 4, table 1). Though, no significant difference in mean values for CCC between poor and non-poor entities are not a satisfying explanation to why CCC is not included in the final combination of key ratios.

orders aimed at measuring net working capital changes not justified by changes in orders. We believed that the effect could come gradually and that a trend of a slightly inefficient management in t-1 could help explain poor WCD in t. However, no significant trend of a graduate increase in inefficient management of net working capital can be seen (see Appendices 4, table 1) and it appears as the variable is not significantly helpful in predicting poor WCD even when allowing for interrelation with other variables.

8. Discussion

Our study results in three models to predict poor WCD. The choices we have made to investigate the possibility to predict poor WCD, create implications both in terms of results achieved and of the use of the models. Below section discusses our choices made and their implications.

8.1 Separation of poor and non-poor entities

Our study contributes with evidence that it is possible to predict poor WCD on a quarterly basis using accounting based financial information. However, our decision to use a case company to estimate the models creates limitations in terms of generalization, meaning that the models may not be directly applicable to other multinational industrial companies. The models can only be viewed as generic if the case company is representative for other multinational industrial companies. Since poor and non-poor entities have been defined partly based on specific information for the case company, i.e. the time lag between orders received and net working capital, the models may not be applicable to other industrial companies if the time lags differ. In that case, to predict poor WCD with best accuracy, companies should adjust the approach used to separate poor and non-poor entities so that it reflects their specific time lags in order to estimate a model. Further, we only investigate one form of inefficient WCM, i.e. poor WCD, meaning we do not fully capture the issues of WCM on a company's agenda. Many other approaches to capture the broader meaning of efficient WCM exist, and we encourage further developments of how to define which entities that can be considered poor in terms of inefficient WCM. As the models may not be directly applicable to other companies, limitations exist in the contribution of helping multinational industrial companies predicting poor WCD.

8.2 Internal data

Furthermore, the use of the models may not only be limited to the case company (worst case), but are also restricted to internal use as they are based on accounting based financial information on an operating entity level, information that is not public. Entities on operating entity level are the ones that impact and control WCD which is the reason for choosing to predict poor WCD on this level. Information on legal entity level was not used as the legal entities include several operating entities with different activities. Investors and other stakeholders could use a model like this to evaluate a company's financial strength and likelihood of financial distress. However, they do not have access to internal information and would have to use data on a legal entity level. Also, they would not be able to access the quarterly data in time to predict poor WCD the coming quarter due to the publication time lag of about three months. This means that they would probably have to use data from two quarters in advance to predict poor WCD, i.e. data from t-2 to predict poor WCD in t. These two factors would most likely decrease the prediction power to the extent that the models would not be able to predict poor WCD with enough accuracy.

8.3 Choice of initial selection of key ratios

The choice of initial selection of key ratios to predict poor WCD is critical. The independent variables chosen to try to predict poor WCD affects both the outcome and restricts what can be achieved in terms of the models' prediction powers. If important information is left out, the models' prediction powers will not be as good as it possibly could become. It is clear that objections can be made to the relatively easy definitions of different accounting ratios used in the model. Also, as no former studies predicting poor WCD exists, the initial selection of key ratios can further be questioned as the choice could not be validated through former researchers' choices.

8.3.1 Data availability

It can be claimed that logit analysis with only accounting key ratios is an unrealistic and/or incomplete prediction model, a critique difficult to justify. Other sources of information should be included to address the critique. We aimed to create a model using commonly used and accessible information already available in a company's financial system. Though, if collection of additional sources of information had been performed, it could have been added to the company's system. However, the additional sources of information most likely need to be up-to-date, which would impact the models' ease of use in the future.

Additional information that could be helpful in predicting poor WCD is distance (door-to-door shipment) and country specific payment terms. Both of these factors could contribute to what appears as poor WCD, although entities may have no ability to affect them. Hence, distance may contribute to longer CCC and higher inventory for example and praxis of payment terms in different countries affects accounts receivables and CCC as well. These variables would have been useful estimating the models, however, not as predicting variables but rather as control variables. If controlled for, higher prediction power could be a result.

Even though we divided the data on CCs and PCs, an additional approach would be to divide the data based on business areas to investigate if prediction power improves. However, separated data on business area for operating entities in the financial system was not available.

8.4 Finding the final combination of key ratios in the prediction models

To reduce the number of explanatory variables in the models, we used the stepwise forward and backward function in STATA, as used by for example Dewaelheyns & van Hulle (2006). We wanted to reduce the number of explanatory variables to make the models easier to use for the company. Stepwise is an easy and available method in STATA to reduce the number of variables without a significant reduction in likelihood ratio. However, as discussed, the approach comes with the limitation of possible biased selection of variables.

8.5 Further research

Our study is a first effort to predict poor WCD and we encourage further research on this subject. As mentioned, one of the limitations of our results is the generalizability of the models for other industrial companies. Our models could be tested in other industrial companies to validate if the models can be used within other industrial firms or if company specific models in fact are preferable. Or, to ensure a more generic model, several companies within the same industry should be used to estimate a model predicting poor WCD. However, still internal data is suggested to be used to avoid the time lag of public reports. Even if using companies within the same industry, it would be interesting to see if the prediction of poor WCD is affected by country and thus models based on national companies are encouraged. By doing so, praxis of payment terms would more easily be captured as well.

As mentioned, we wanted to create a tool for companies to help them solve issues of WCM. Efficient WCM has been shown to affect both profitability and liquidity. Hence, the ability to predict poor WCD, a form of inefficient WCM, could create cost savings for the companies and it would be of interest to quantify these savings more specifically than what we have done by investigating the average error costs. We suggest a post study where the savings are quantified using the prediction model, which would validate the tool created to help companies in terms of WCM. Also, actions taken to prevent poor WCD can be observed and evaluated.

9. Conclusion

We investigate if poor WCD can be predicted using accounting based financial information in the form of key ratios. The WCD is considered poor if the change in net working capital is not driven by an underlying change in customer orders. The study is performed using operating entities in our case company, a Swedish multinational industrial company, resulting in 2,420 entity-quarter observations covering year 2009-2013. Three models to predict poor WCD on a quarterly basis among operating entities are created using logit analysis; one original model including all observations and two models (CC and PC) separated on the two activities selling and manufacturing. The original model results in a prediction power of 79.21% and the CC and PC models of 81.10% and 76.90% respectively. Thus, using accounting based financial information to predict poor WCD on a quarterly basis among operating entities is possible. The prediction powers(1) based on mean errors, f(1), are lower than what achieved in previous studies predicting bankruptcy using accounting based financial information. The key ratios found explanatory to predict poor WCD are asset turnover, inventory intensiveness, asset structure, asset liquidity, an entity's historical frequency of poor quarters, growth in equity and growth in debt.

We expected the ability to predict poor WCD would improve when separating the entities on CCs and PCs as their activities differ, this was however not confirmed as the separate models for CCs and PCs are not significantly better in terms of prediction power compared to the original model. However, the models' prediction powers were evaluated based on both minimized mean error and average error cost. The model can make two types of errors; classify poor entities as non-poor (type I errors) or classify non-poor entities as poor (type II errors). When minimizing mean error, f(2), that weights the two types of errors based on the proportion of poor and non-poor entities in the sample, the type I and type II error rates are affected by these proportions. Presented above are prediction powers(2) when minimizing mean error(f2), however, if the company has a preference for avoiding one of the two types of errors more than the other, a better evaluation of the models' prediction powers is the average error cost.

Efficient WCM is argued by theory and shown through empirical results to improve both profitability and liquidity, therefore type I errors are preferably avoided. Evaluating the models based on average error cost, the usefulness of the models increase significantly the higher the cost of type I errors are compared to type II errors. Also, using this approach illustrates the importance of separating the data on CCs and PCs since fewer type I errors are achieved for the separate models compared to the original model, especially for the PC model, and separate models are therefore better in terms of cost savings for the company.

One of the most important issues on a company's agenda is WCM, where our case company's specific problem in terms of poor WCD illustrates one of the issues faced by companies. We aimed to create a model predicting poor WCD, a form of inefficient WCM, which can be used as a tool to prevent inefficient WCM and also increase awareness and control of WCM. Our models are shown to have prediction powers and thus can be helpful to companies. However, as data from a case company have been used, the models may not be directly applicable to other industrial companies without adjustments and re-estimations. Our study provides evidence that prediction of poor WCD using accounting based financial information is possible. Once the model is estimated to fit the specific company, the use of the model will increase the awareness of inefficient WCM through detection of poor WCD, and in best case enable the company to prevent it which could result in better liquidity and profitability.

10. Bibliography

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, *23*(4), 589-609.

Altman, E. I. (1971). *Corporate bankruptcy in America*. Lexington, MA: Heath Lexington Books.

Altman, E. I., Haldeman, R. G., & Narayanan, P. (1977). ZETA< sup> TM</sup> analysis A new model to identify bankruptcy risk of corporations. *journal of banking & finance*, *1*(1), 29-54.

Altman, E. I., & Loris, B. (1976). A FINANCIAL EARLY WARNING SYSTEM FOR OVER-THE-COUNTER BROKER-DEALERS. *The journal of Finance*, *31*(4), 1201-1217.

Baumol, W. J. (1952). The transactions demand for cash: An inventory theoretic approach. *Quarterly journal of Economics*, *66*(4), 545-556.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of accounting research*, 71-111.

Beaver, W. H., Kennelly, J. W., & Voss, W. M. (1968). Predictive ability as a criterion for the evaluation of accounting data. *Accounting Review*, 675-683.

Berkson, J. (1944). Application of the logistic function to bioassay. *Journal of the American Statistical Association* 39, 357.65.

Blum, M. (1974). Failing company discriminant analysis. *Journal of accounting research*, 1-25.

Burkart, M., & Ellingsen, T. (2004). In-kind finance: A theory of trade credit. *The American Economic Review*, *94*(3), 569-590.

Chan, R. C. (2010). *A Working Capital Theory of the Firm with Empirical Evidence* (Doctoral dissertation, University of Oxford).

Chava, S., & Jarrow, R. A. (2004). Bankruptcy prediction with industry effects. *Review of Finance*, *8*(4), 537-569.

Corey, S., Campbell, S. N., & Jones, K. T. (2013). Analyzing Liquidity: Using the Cash Conversion Cycle. *Journal of Accountancy***.** May2013, Vol. 215 Issue 5, p44-48. 5p. 1 Color Photograph, 1 Chart, 2 Graphs.

Dambolena, I. G., & Khoury, S. J. (1980). Ratio stability and corporate failure. *The Journal of Finance*, *35*(4), 1017-1026.

Deakin, E. B. (1972). A discriminant analysis of predictors of business failure. *Journal of Accounting Research*, 167-179.

Deloof, M. (2003). Does working capital management affect profitability of Belgian firms?. *Journal of Business Finance & Accounting*, *30*(3-4), 573-588.

Derksen, S., & Keselman, H. J. (1992). Backward, forward and stepwise automated subset selection algorithms: Frequency of obtaining authentic and noise variables. British Journal of Mathematical and Statistical Psychology, 45(2), 265-282.

Dewaelheyns, N., & Van Hulle, C. (2006). Corporate failure prediction modeling: Distorted by business groups' internal capital markets?. *Journal of Business Finance & Accounting*, *33*(5-6), 909-931.

Dewing, A. S. (1941). *The financial policy of corporations* (Vol. 1). Ronald Press.

Donaldson, G. (1969). Strategy for financial emergencies. *HARVARD BUSINESS REVIEW, P 67-79, NOV-DEC 1969. 2 CHARTS, 1 REF.*

Dong, H. P., & Su, J. T. (2010). The relationship between working capital management and profitability: a Vietnam case. *International Research Journal of Finance and Economics*, *49*(49), 62-71.

Edmister, R. O. (1972). An empirical test of financial ratio analysis for small business failure prediction. *Journal of Financial and Quantitative Analysis*, *7*(02), 1477-1493.

Elam, R. (1975). The effect of lease data on the predictive ability of financial ratios. *Accounting Review*, 25-43.

Eljelly, A. M. (2004). Liquidity-profitability tradeoff: an empirical investigation in an emerging market. *International Journal of Commerce and Management*, *14*(2), 48-61.

EY. (2013). *Working Capital Optimization*. Canadian Financial Executives Research Foundation. *Available at ISBN# 978-1-927568-05-7.*

Falope, O. I., & Ajilore, O. T. (2009). Working Capital Management and Corporate Profitability: Evidence from Panel Data Analysis of Selected Quoted Companies in Nigeria. *Research journal of business management*, *3*(3).

Fazzari, S. M., & Petersen, B. C. (1993). Working capital and fixed investment: new evidence on financing constraints. *The RAND Journal of Economics*, 328-342.

Foster, G. (1986). *Financial Statement Analysis.* Prentice-Hall International, 2nd edition.

Garcia, J. L., Martins, F. V., & Brandão, E. (2011). The Impact of Working Capital Management upon Companies' Profitability: Evidence from European Companies. *Available at SSRN 2165210*.

García-Teruel, P. J., & Martínez-Solano, P. (2007). Effects of working capital management on SME profitability. *International Journal of Managerial Finance*, *3*(2), 164-177.

Gill, A., Biger, N., & Mathur, N. (2010). The Relationship Between Working Capital Management And Profitability: Evidence From The United States. *Business & Economics Journal*.

Hansson, S., Arvidson, P., & Lindquist, H. (2006). *Företags-och räkenskapsanalys*. Studentlitteratur.

Horowitz, J. L., & Savin, N. E. (2001). Binary response models: Logits, probits and semiparametrics. *Journal of Economic Perspectives*, *15*(4), 43-56.

Hoshi, T., Kashyap, A., & Scharfstein, D. (1991). Corporate structure, liquidity, and investment: Evidence from Japanese industrial groups. *The Quarterly Journal of Economics*, *106*(1), 33-60.

Hu, B., Shao, J., & Palta, M. (2006). Pseudo-R^ 2 in logistic regression model. *Statistica Sinica*, *16*(3), 847.

IASB. (2007). Information for observers. Board Meeting: February 22nd 2007, London. Project: Financial Statement Presentation (Phase B). Subject: Presentation of liquidity information (Agenda Paper 9). *International Accounting Standards Board.* Available at http://www.ifrs.org/Meetings/MeetingDocs/IASB/2007/February/22nd/FSP-0702-AP9-obs.pdf Accessed: May 4th

Jensen, M. C. (2010). Value maximization, stakeholder theory, and the corporate objective function. *Journal of applied corporate finance*, *22*(1), 32-42.

Jolliffe, I. (2005). *Principal component analysis*. John Wiley & Sons, Ltd.

Joy, O. M., & Tollefson, J. O. (1975). On the financial applications of discriminant analysis. *Journal of Financial and Quantitative Analysis*, *10*(05), 723-739.

Ketz, J. E. (1978). The effect of general price-level adjustments on the predictive ability of financial ratios. *Journal of Accounting Research*, 273-284.

Koller, T., Goedhart, M., & Wessels, D. (2010). *Valuation: measuring and managing the value of companies* (Vol. 499). John Wiley and Sons.

Leal, C. P., & Santos, C. (2007). Insolvency prediction in the portuguese textile industry. *European Journal of Finance and Banking Research*, *1*(1).

Long, J. S., & Freese, J. (2003). Regression models for categorical and limited dependent variables using Stata. *Stata Press, Revised Edition.*

Long, J. S., & Freese, J. (2006). Regression models for categorical and limited dependent variables using Stata. *Stata Press, College Station, TX*.

Long, M. S., Malitz, I. B., & Ravid, S. A. (1993). Trade credit, quality guarantees, and product marketability. *Financial Management, 22*(4).

Magnac, T. (2006). Logit models of individual choices.

Mathuva, D. M. (2010). The Influence of Working Capital Management Components on Corporate Profitability: A survey on Kenyan Listed Firms. *Research Journal of Business Management*, *4*(1).

McFadden, D. (2001). Economic choices. *American Economic Review*, 351-378.

Meltzer, A. H. (1960). Mercantile credit, monetary policy, and size of firms.

Mensah, Y. M. (1983). The differential bankruptcy predictive ability of specific price level adjustments: some empirical evidence. *Accounting Review*, 228-246.

Miller, M. H., & Orr, D. (1966). A Model of the Demand for Money by Firms. *The Quarterly Journal of Economics, 80*(3), 413-435.

Moyer, R. C. (1977). Forecasting financial failure: a re-examination. *Financial Management*, 11-17.

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

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

Nazir, M. S., & Afza, T. (2009). Impact of Aggressive Working Capital Management Policy on Firms' Profitability. *IUP Journal of Applied Finance*, *15*(8).

Nobanee, H. (2009). Working capital management and firm's profitability: an optimal cash conversion cycle. *Available at SSRN 147123*.

Nobanee, H., & AlHajjar, M. (2009). A note on working capital management and corporate profitability of Japanese firms. *Available at SSRN 1433243*.

Norton, C. L., & Smith, R. E. (1979). A comparison of general price level and historical cost financial statements in the prediction of bankruptcy. *Accounting Review*, 72-87.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*, 109-131.

Padachi, K. (2006). Trends in working capital management and its impact on firms' performance: an analysis of Mauritian small manufacturing firms. *International Review of business research papers, 2*(2), 45-58.

Penman, S. (2013). *Financial Statement Analysis & Security Valuation*. McGrawHill-Irwin, 5th edition.

Preve, L. & Sarria-Allende, V. (2010) *Working capital management*. New York: Oxford University Press, Inc.

Raheman, A., & Nasr, M. (2007). Working capital management and profitability–case of Pakistani firms. *International review of business research papers*, *3*(1), 279-300.

REL. (2012). Most Companies Fail to Accurately Forecast Working Capital Needs And the Cash to Support Them, Says New Study by REL Consulting. *The Hackett Group, Inc. April 26th 2012*. Available at http://www.thehackettgroup.com/about/research-alerts-press-releases/2012/04262012-companies-fail-accurately-forecast.jsp Accessed March 26th 2014 Accessed March 25th.

Sagan, J. (1955). Toward a theory of working capital management. *The Journal of finance*, *10*(2), 121-129.

Samiloglu, F., & Demirgunes, K. (2008). The effect of working capital management on firm profitability: Evidence from Turkey. *The International Journal of Applied Economics and Finance*, *2*(1), 44-50.

Sharma, D. (2009). *Working Capital Management*. Himalaya Publishing House.

Shin, H. H., & Soenen, L. (1998). Efficiency of working capital management and corporate profitability. *Financial practice and education, 8*, 37-45.

Sinkey, J. F. (1975). A multivariate statistical analysis of the characteristics of problem banks. *The Journal of Finance*, *30*(1), 21-36.

Skogsvik, K. (1988a). *Prognos av finansiell kris med redovisningsmatt: en jämförelse mellan traditionell och inflationsjusterad redovisning* (Doctoral dissertation, Handelshögskolan i Stockholm).

Skogsvik, K. (1988b). Predicting failure by means of financial ratios. *Skandinaviska Enskilda Banken Quarterly Review, 2*.

Skogsvik, K. (1990). Current cost accounting ratios as predictors of business failure: The Swedish case. *Journal of Business Finance & Accounting*, *17*(1), 137-160.

Skogsvik, K.(2002). A tutorial on residual income valuation and value added valuation. SSE/EFI Working Paper Series in Business Administration No 1999, 10.

Skogsvik, K. (2013). *Accounting ratio analysis in a capital market context.* Lecture 1, course 3307 Advanced Financial Analysis, April 2nd 2013 at the Stockholm School of Economics

Skogsvik, K., & Skogsvik, S. (2013). On the choice based sample bias in probabilistic bankruptcy prediction. *Investment Management and Financial Innovations10 (1)*, 29-37.

Smith, K. V. (1973). State of the art of working capital management. *Financial management*, 50-55.

Train, K. Discrete choice methods with simulation. 2003. *Cambridge, United*, *595*.

Upton, G., & Cook, I. (1996). *Understanding statistics*. Oxford University Press.

Zariyawati, M. A., Annuar, M. N., Taufiq, H., & Rahim, A. A. (2009). Working capital management and corporate performance: Case of Malaysia. *Journal of Modern Accounting and Auditing*, *5*(11), 47-54.

Zavgren, C. V. (1985). Assessing the vulnerability to failure of American industrial firms: a logistic analysis. *Journal of Business Finance & Accounting*, *12*(1), 19-45.

Appendices

Appendix 1

The funding need in a company according to Penman (2013) can be written as:

$$\mathrm{C_t} - \mathrm{I_t} - \Delta\mathrm{NFA_t} + \mathrm{NFI}_t = \mathrm{d}_t \tag{1}$$

and

$$\mathrm{C_t} - \mathrm{I_t} = \mathrm{OI_t} - \Delta\mathrm{NOA_t} \tag{2}$$

and thus,

$$\mathrm{OI}_t - \Delta\mathrm{NOA}_t - \Delta\mathrm{NFA}_t + \mathrm{NFI}_t = \mathrm{d}_t \tag{3}$$

where

$\mathrm{C_t}$ = Cash flow from operations at time t

$\mathrm{I_t}$ = Cash investments at time t

$\mathrm{NFA_t}$ = Net financial assets

NFI_t = Net financial income

d_t = Net cash flow to shareholders

$\mathrm{NOA_t}$ = Net operating assets at t

Usually $\mathrm{NFA} < 0$ and is then a net financial obligation (NFO) and $\mathrm{NFI} < 0$ and thus a net financial expense (NFE).

(Penman, 2013)

A net financial obligation (NFO) will hereafter called net debt (ND) and net operating assets (NOA) is called operating net assets (ONA).

The formula for a company's funding need can then be written as:

$$\mathrm{OI}_t - \Delta\mathrm{ONA}_t + \Delta\mathrm{ND}_t - \mathrm{NFE}_t = \mathrm{d}_t \tag{4}$$

where

OI_t = Operating income at time t

ONA_t = Operating net assets at time t

$\mathrm{ND_t}$ = Net debt at time t = (Debt-Financial assets) at time t

NFE_t= Net financial expenses

This can be rewritten as:

$$(\mathrm{OI}_t + \mathrm{Depr_t}) - (\mathrm{Inv_t} + \Delta(\mathrm{net\ WC})_\mathrm{t}) + \Delta\mathrm{ND}_t - (\mathrm{r_{ND}} * \mathrm{ND_t}) = \mathrm{d}_t \tag{5}$$

where

$\mathrm{Depr_t}$ = Depreciation at time t

$\mathrm{Inv_t}$ = Net cash investments in assets not included in working capital at time t

$\Delta(\mathrm{net\ WC})_\mathrm{t}$ = $\Delta(\mathrm{net\ working\ capital_t})$ = $(\mathrm{net\ WC_t} - \mathrm{net\ WC_{t-1}})$

$=$ Δ(operating current assets – operating current liabilities) at time t

$(\mathrm{r_{ND}} * \mathrm{ND_t}) = \mathrm{NFE}_t$

and $\mathrm{r_{ND}}$ = Interest rate on net debt

$\mathrm{d}_t = \mathrm{DIV_t} + \mathrm{SR_t} - \mathrm{IS_t}$

$\mathrm{DIV_t}$ = Dividends at time t

$\mathrm{SR_t}$= Share repurchase at time t

$\mathrm{IS_t}$= Issuance of shares

Thus, the external funding need in an entity (with no possibility to share repurchase or issuance of shares on operating entity level), and taking taxes into account, can therefore be rewritten as:

$$\Delta \mathrm{ND}_t = \mathrm{Inv}_t + \Delta(\mathrm{net\ WC})_t - [\mathrm{OI}_t(1 - \mathrm{T}_c) + \mathrm{Depr}_t - (\mathrm{r}_{\mathrm{ND}} * \mathrm{ND}_t)(1 - \mathrm{T}_c)] + \mathrm{DIV}_t \qquad (6)$$

where

T_c = Tax rate

Rearrangement of formula (6):

$$\Delta(\mathrm{net\ WC})_t - [\mathrm{OI}_t(1 - \mathrm{T}_c) + \mathrm{Depr}_t - (\mathrm{r}_{\mathrm{ND}} * \mathrm{ND}_t)(1 - \mathrm{T}_c)] = \Delta \mathrm{ND}_t - \mathrm{Inv}_t - \mathrm{DIV}_t \qquad (7)$$

Appendix 2

Table 1

Non-poor and poor quarters per entity

Entity	Non-poor quarters	Poor quarters	Percent poor quarters per entity
1	7	2	0.22
2	11	5	0.31
3	3	1	0.25
4	11	3	0.21
5	11	4	0.27
6	1	0	0.00
7	12	4	0.25
8	5	4	0.44
9	8	3	0.27
10	10	3	0.23
11	12	4	0.25
12	12	4	0.25
13	11	4	0.27
14	13	3	0.19
15	12	4	0.25
16	11	3	0.21
17	10	4	0.29
18	12	4	0.25
19	8	2	0.20
20	6	3	0.33
21	9	3	0.25
22	10	4	0.29
23	1	1	0.50
24	11	4	0.27
25	6	3	0.33
26	6	2	0.25
27	1	0	0.00
28	2	0	0.00
29	8	1	0.11
30	11	4	0.27
31	1	0	0.00
32	2	0	0.00
33	1	0	0.00
34	12	4	0.25
35	11	4	0.27

36	9	4	0.31
37	12	4	0.25
38	2	1	0.33
39	10	3	0.23
40	8	2	0.20
41	8	2	0.20
42	11	4	0.27
43	5	3	0.38
44	11	4	0.27
45	1	0	0.00
46	10	5	0.33
47	6	3	0.33
48	11	4	0.27
49	8	4	0.33
50	2	1	0.33
51	12	4	0.25
52	5	2	0.29
53	3	2	0.40
54	12	4	0.25
55	8	3	0.27
56	1	0	0.00
57	10	4	0.29
58	12	4	0.25
59	4	2	0.33
60	11	4	0.27
61	10	4	0.29
62	6	1	0.14
63	11	0	0.00
64	12	4	0.25
65	8	2	0.20
66	4	2	0.33
67	6	3	0.33
68	1	1	0.50
69	7	3	0.30
70	3	1	0.25
71	2	1	0.33
72	12	4	0.25
73	12	4	0.25
74	11	3	0.21
75	10	4	0.29
76	8	3	0.27

77	5	2	0.29
78	11	4	0.27
79	12	4	0.25
80	11	3	0.21
81	7	2	0.22
82	3	1	0.25
83	5	2	0.29
84	2	0	0.00
85	7	2	0.22
86	11	3	0.21
87	7	2	0.22
88	11	4	0.27
89	10	4	0.29
90	11	3	0.21
91	2	1	0.33
92	9	4	0.31
93	8	3	0.27
94	11	4	0.27
95	8	1	0.11
96	10	4	0.29
97	5	2	0.29
98	1	0	0.00
99	10	4	0.29
100	3	1	0.25
101	2	1	0.33
102	5	2	0.29
103	2	2	0.50
104	6	1	0.14
105	2	1	0.33
106	3	1	0.25
107	3	4	0.57
108	12	2	0.14
109	5	4	0.44
110	8	4	0.33
111	1	4	0.80
112	12	3	0.20
113	12	3	0.20
114	8	4	0.33
115	12	3	0.20
116	11	4	0.27
117	7	4	0.36

118	9	4	0.31
119	12	4	0.25
120	12	2	0.14
121	11	4	0.27
122	8	2	0.20
123	7	1	0.13
124	7	3	0.30
125	12	2	0.14
126	2	4	0.67
127	11	1	0.08
128	2	4	0.67
129	7	1	0.13
130	12	2	0.14
131	12	4	0.25
132	5	1	0.17
133	10	4	0.29
134	3	1	0.25
135	9	3	0.25
136	8	3	0.27
137	9	5	0.36
138	12	4	0.25
139	11	4	0.27
140	10	2	0.17
141	12	4	0.25
142	2	2	0.50
143	2	1	0.33
144	9	4	0.31
145	6	1	0.14
146	1	0	0.00
147	12	3	0.20
148	10	2	0.17
149	9	3	0.25
150	8	2	0.20
151	3	1	0.25
152	7	1	0.13
153	3	1	0.25
154	9	2	0.18
155	10	4	0.29
156	12	4	0.25
157	5	1	0.17
158	4	0	0.00

159	7	1	0.13
160	12	4	0.25
161	2	1	0.33
162	3	1	0.25
163	12	4	0.25
164	7	2	0.22
165	12	4	0.25
166	10	4	0.29
167	1	1	0.50
168	1	4	0.80
169	1	2	0.67
170	5	4	0.44
171	12	4	0.25
172	6	4	0.40
173	12	4	0.25
174	12	4	0.25
175	12	4	0.25
176	2	1	0.33
177	12	4	0.25
178	9	4	0.31
179	10	4	0.29
180	12	4	0.25
181	8	3	0.27
182	4	2	0.33
183	11	4	0.27
184	10	3	0.23
185	3	4	0.57
186	8	1	0.11
187	12	4	0.25
188	3	1	0.25
189	9	2	0.18
190	12	3	0.20
191	5	0	0.00
192	2	0	0.00
193	10	4	0.29
194	11	3	0.21
195	12	4	0.25
196	2	1	0.33
197	12	4	0.25
198	11	4	0.27
199	7	3	0.30

200	12	4	0.25
201	12	4	0.25
202	12	3	0.20
203	12	4	0.25
204	7	3	0.30
205	12	4	0.25
206	11	4	0.27
207	11	3	0.21
208	5	3	0.38
209	12	4	0.25
210	12	4	0.25
211	11	4	0.27
212	9	4	0.31
213	11	5	0.31
214	7	3	0.30
215	1	0	0.00
216	12	4	0.25
217	12	4	0.25
218	9	3	0.25
219	7	3	0.30
220	2	1	0.33
221	12	4	0.25
222	11	3	0.21
223	1	0	0.00
224	2	0	0.00
225	6	3	0.33
226	7	3	0.30
227	2	0	0.00
228	11	4	0.27
229	9	3	0.25
230	2	0	0.00
	1795	625	

Appendix 3

The a priori probability, L, can be defined as:

$$L(\delta) = \sum_{i \in S_1} \log P(AR_i, \delta) + \sum_{i \in S_2} \log(1 - P(AR_i, \delta)) \qquad (1)$$

where

S_1=the set of poor entities

S_1=the set of non-poor entities

(Ohlson, 1980)

When maximizing L with regards to the coefficients, δ_i, using an iterative process called maximum likelihood estimation optimal values of $\delta_{1,}$ δ_2,… δ_i can be estimated (Skogsvik, 1988a). This was done in our study by using the statistical package STATA.

Appendix 4

Table 1

Mean values for poor and non-poor entities in t-1 and t-statistics for the difference between them

	Original			CC			PC		
Variables	Non-poor	Poor	t-Statistics	Non-poor	Poor	t-Statistics	Non-poor	Poor	t-Statistics
ROA	0.083	0.063	0.000	0.081	0.052	0.000	0.359	0.089	0.983
ROE	0.449	0.435	0.529	0.425	0.407	0.454	1.858	0.502	0.933
rd	0.007	0.006	0.000	0.007	0.006	0.000	0.022	0.005	0.017
taxq	0.192	0.188	0.769	0.201	0.195	0.667	0.769	0.173	0.786
assetturnover	10.251	0.932	0.000	1.374	0.987	0.000	2.374	0.796	0.007
invint	0.267	0.282	0.168	0.224	0.238	0.225	1.107	0.398	0.821
cashpos	0.384	0.376	0.719	0.387	0.385	0.928	1.403	0.354	0.633
shortliq	1.828	1.850	0.606	1.793	1.828	0.424	5.038	1.989	0.756
assetstructure	0.175	0.180	0.583	0.129	0.134	0.485	0.846	0.279	0.798
assetliq	0.397	0.405	0.408	0.341	0.344	0.716	1.046	0.550	0.718
finstructure	0.401	0.399	0.804	0.387	0.381	0.585	0.938	0.441	0.847
businessg	0.025	0.022	0.789	0.031	0.025	0.669	0.456	0.015	0.761
geq	0.050	0.013	0.000	0.041	-0.006	0.000	0.408	0.056	0.342
gdebt	-0.022	-0.004	0.184	-0.026	0.037	0.000	0.395	-0.084	0.001
size	11.458	11.519	0.567	11.195	11.240	0.665	13.016	13.064	0.847
CCC	40.596	11.489	0.136	-44.384	-92.410	0.105	116.986	76.609	0.745
orders	0.355	0.402	0.860	0.313	0.363	0.871	10.858	0.494	0.963
poorWCDfreq	0.380	0.322	0.000	0.371	0.312	0.000	0.875	0.346	0.000