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The Use of Corporate Ledger Information in Payment Behavior Prediction - Evidence from the Finnish Construction Industry

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THE USE OF CORPORATE LEDGER INFORMATION IN PAYMENT BEHAVIOR PREDICTION
– Evidence from the Finnish Construction Industry

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ABSTRACT

This paper provides new insights into payment behavior prediction by using daily ledger data from a case company. The results indicate that a model based on ledger information is more accurate and efficient in future payment failure prediction than models traditionally based on financial and background variables. More specifically, the results implicate that a company benefits the most from credit risk rating services when its own ledger data are used as a part of the rating scoring model. In addition, the results have three implications. First, ledger information can be used in the future to create more accurate and up-to-date credit rating scores, which reduces the dependency over publicly available information. Second, the length of the client firm-creditor firm relationship seems to significantly reduce problems of informational asymmetry. Third, problems of asymmetric information, such as adverse selection, lemon's problem, moral hazard and agency costs could be significantly reduced in the future using a shared information pool deriving from corporate ledgers.

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1 Introduction

Financial distress, likelihood of bankruptcy and default in payments have long been in the centre of interest in the credit risk management field. However, the financial crisis and the sovereign debt crisis of the 21st century have increased the demand for an accurate method that helps companies predict not only bankruptcy but also possible signals of the way towards financial distress by looking at customers' payment behavior. In addition to banks, for example trade credit managers are known to use models to predict corporate failure as part of their credit decision-making process. Nevertheless, the primary interest still remains in the customers' payment behavior: will a firm pay its bills on time? So far, the information about a potential new corporate client's payment history has only been accessible for companies dealing with a third party, such as a credit insurer, who has accumulated private knowledge from a large number of suppliers. On the other hand, in the UK for instance, scores describing past payment behavior have become more and more available in credit reports. (See, also, Wilson, Summers & Hope, 2000).

1.1 Background and Motivation for the Study

This paper analyzes whether the knowledge of payment behavior and its prediction have importance in two contexts: that of payment delays implying a payment pattern rather than financial instability, or that of payment delays as a signal of financial troubles, or both. In addition to financial distress, payment failure might be a signal of a firm's misuse of its business relationship with the creditor company; larger client firms generally bring more cash flow to a company, and higher purchase power might lead to arrogant behavior where investment opportunities are prioritized over prompt payment of trade creditors. Poor payment behavior, or failure to pay on time, may also be a sign of the use of trade credit as extended credit (Wilson & Summers, 2000). This thesis attempts to analyze whether payment failure can be predicted accurately with payment history derived from a corporate ledger, or whether it can be related to financial difficulties. The results of this study could be useful in the development of modern credit rating systems and in the credit assessment process of any company. The results could be especially useful for the Finnish trade credit sector as the application of payment behavior information is trailing some other countries where payment indices are vastly used.[1]

This thesis considers the contribution that daily client billing data and background information, gathered from a case company's corporate ledger, can make to payment failure prediction at the corporate level. More specifically, I study whether a company's internal ledger data has significant influence on the accuracy of a risk estimation model, even over external information, when predicting that company's client firms' payment delays. In addition, I study if a model using ledger data can be improved with data from a Finnish credit rating agency, Asiakastieto Ltd; I analyze both the value that individual financial and background variables can add to a model using ledger data, and the use of the rating agency's existing rating scores in payment failure prediction.

Asiakastieto Ltd's generic credit risk model uses ledger data to some extent, in addition to financial and background variables. I compare the prediction power of the current rating scores[2] – based on external data from public financial statements, publicly available registries and a limited pool of corporate ledgers – to the contribution of the variables developed in this study – based on internal ledger data from a case company. Thus the objective of this paper is to study whether an interactive approach in rating scoring, that involves the customer company's own input, performs better compared to a more generic approach.

As each company has unique business characteristics and a unique set of clients, it is expected that a company's own contribution is essential in the modelling of its client firms' payment behavior

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[1] See for instance Wilson, Summers and Hope (2000) for research on the use of a German payment index, Paydex.

[2] Asiakastieto Ltd calls their letter ratings as Rating Alfa: the ratings vary from the highest score AAA to the lowest score C.

or payment difficulties, in addition to external data provided by a rating agency. This paper also analyzes the differences between poor payment behavior, defined by a 'payment failure event', and an actual default in payments; a firm that constantly pays its bills late may well have a healthy balance sheet and no reported defaults in payments – it might simply use its scale of economics to profit from other investment opportunities that more than cover the expenses of paying late. Thus a firm that systematically pays its bills after the due date may as well be a financially stable firm with merely a bad habit. However it is as likely that poor paying habits are related to weak financials and signal upcoming financial distress. The purpose of this study is to examine whether payment failure, measured with unregistered and systematic significantly late payments, can be related to financial difficulties measured by selected financial ratios and Asiakastieto Ltd's scores, and whether it can be predicted with payment history. This thesis is expected to provide useful insights for the development of a leading Finnish credit rating agency Asiakastieto Ltd's credit rating system. However the results of this study may be used for the development of any independent rating system as they all cover fundamentally the same principles (Saraç, 2010).

My empirical tests proceed as follows; firstly using the binary regression framework, I analyze the probability of systematic and severe payment delays. I relate the likelihood of failure to pay on time[3] to the variables used to describe the client firms' background, financials and past payment behavior. Secondly, I test whether payment history variables derived from the ledger data possess the most prediction power in payment failure prediction, even relative to the background and financial variables. Moreover, I study the combinations of different types of variables, as there may be differences in the classification accuracy of the models depending on how well each type of data links to the dependent variable chosen.

First, I describe the main differences between the types of independent variables and the study's definition of failure, compared to prior literature, and second I analyze the effects of different

[3] From here onwards failure to pay on time is replaced by "payment failure" or simply "failure" in the discourse of this thesis. Thus firms that cross a certain limit of late payments set by Company X, are denoted as failed while others are denoted as non-failed.

variable combinations in the binary logistic regression framework in more detail. Finally, I compare the results of different models and analyze which combinations of variables perform best together and which information is the most accurate in payment failure prediction.

1.2 Agenda of the Paper

This study seeks to examine the use of ledger data in payment behavior prediction and the possible pros of the new approach compared to the traditional models using primarily financial variables. Furthermore, I extend the research on corporate failure prediction with non-financial variables and test whether the use of client firms' recent payment history is able to increase the accuracy of a credit risk model based on general information on the same clients. The goal of the research is, using the binary logistic framework[4], to analyze the probability of an individual client firm failing in its payments; the status of a poor payer, denoted as a failed firm, is the dependent variable. The dependent variable 'payment failure' takes the value of one (1) if a client firm continuously[5] pays its bills more than 30 days late, and zero (0) otherwise.

Many prior studies use liquidating bankruptcy or reorganization as the definition of failure[6] while others define failure according to the Basel II framework; a borrower is in default if any payment related to the loan is more than 90 days overdue (Jappelli & Pagano, 2000; Kocenda & Vojtek, 2009). Considering this, the customers defined as failed in this study, that is, firms

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[4] Prior studies have introduced both logistic and hazard models to study corporate failure. Hill, Perry and Andes (1996) argue that movement across company health and financial distress is a dynamic process that consequently requires a dynamic methodology to explain it. For example Turetsky and McEwen (2001) use a Cox proportional hazard model, and Shumway (2001) emphasizes that hazard models are more consistent and accurate than single-period models. Due to the unique nature of the data and its origin, single-period study is the only possibility for this study. However, this technique is widely used and it has been able to yield significant results in the past (See e.g. Back, 2005).

[5] "Continuously" has been defined as a delay in a payment of at least 30 days following the bill's due date and taking place at least three times during June 2011 – May 2012. This definition of payment failure is based on Company X's costs of collection and monitoring versus its profits of interest on late payments. It is hypothesized that the collection procedure of three times turns the profitability of an individual customer to negative, at least in the short term.

[6] See, among others, Altman (1968), Platt and Platt (1991), Chava and Jarrow (2004).

that pay at least three of their bills at least 30 days after the due date, during one calendar year, would not necessarily default in the Basel II framework. Thus all results of this paper are not directly comparable with the previous literature.[7] In Back (2005)'s study, failure is divided into four different categories as follows: (1) bankrupt firms; (2) reorganized firms; (3) firms with recorded payment disturbances; and (4) firms with payment delays, in order to give more room for different types and gravities of failure. Additionally, Beaver (1966) defines failure as a firm's inability to pay its financial obligations as they mature, including firms faced with bankruptcy.

This study differs from prior research with respect to methodology, variables and empirical data. In this paper, all models are estimated using the logistic regression analysis, as shown by Hopwood et al. (1989), Keasey and Watson (1987) and Wilson et. al. (2000), among others. Firstly, the main argument of this study is that data on recent payment history gathered from a corporate ledger not only bring additional information to financial variables but are also more accurate in predicting future payment behavior – payment failure in the context of this study – as the data are up-to-date and not prone to 'window-dressing' or other accounting modification. Moreover, payment failure might not be directly linked to financial distress so that predicting it with traditional methods and variables might not work; a dilemma this study attempts to solve.

Secondly, this paper employs a uniquely measured dependent variable to describe failure. On the one hand payment difficulties and defaults are milder and more common forms of financial distress compared to bankruptcy. On the other hand, payment delays may be a step towards bankruptcy or reorganization if a firm's financial condition deteriorates. (Laitinen & Laitinen, 2009). Furthermore, payments delays may be a sign of a firm's way of using trade credit as a short-term loan (Wilson & Summers, 2000). If this is the case, payment behavior should not

[7] See the test of robustness in Section 4.3 that analyzes the prediction power of ledger variables in the Basel II context.

directly correlate with poor financials – especially as firms tend to use trade credit less during times of financial crises, that is, financial difficulties do not seem to lead to increased use of this type of "extended credit" (see, for example, Lundmark, 2012). This thesis analyzes whether a unique and interactive approach in offering credit risk rating services better captures the risk among a company's clientele. This interactive approach uses a failure definition by the case company itself and uses the company's ledger data to add up to an existing model based on external data. The dependent variable, payment failure, is defined according to the case company's definition of a client relationship's short-term profitability. This thesis aims to find factors behind the early signs of a client firm becoming unprofitable – a firm paying its bills at least 30 days late at least three times within a year, due to either financial difficulties or a behavioral pattern is denoted as, at least temporarily, unprofitable and thus failed.

A practical 'customer-friendly' approach is used to analyze the importance of individual adjustment in rating modelling, based on a rating agency's customer company's clientele, industry and ledger data. As further discussed in Section 3.2, each company has clients paying it better or worse compared to its competitors, due to reasons the company cannot influence. It is typical especially in the construction field, in which the case company operates, that a company at the end of a construction project lifecycle is paid less likely on time compared to a company at the beginning of the cycle as the most essential products are purchased first; failure to pay a company selling the most vital products would most likely end the entire project. As each company's clientele can be assumed to behave differently, it is expected that a unique approach is more accurate in payment behavior prediction.[8] More specifically, this paper aims to analyze the contribution that a company's own ledger data can make to rating scores produced by Asiakastieto Ltd, currently using variables derived from financial and background variables and to some extent using external companies' ledger data as well. In this study, the definition

[8] However, the sharing of private credit information could significantly facilitate credit decisions concerning new client firms; even if firms would on average pay better to Company Z than Company Y, Company Y is yet able to use the information in the shared pool for its own decision making to decide if a firm seeking finance pays well enough considering the possible standard errors due to the life cycle effect of its own products.

of failure is case-company related and unique; thus it is hypothesized that the use of the case company's own ledger improves the prediction power of the current rating scores based on external data.

Thirdly, this study uses a set of variables computed from corporate ledger data, which enables a unique viewpoint into firms' payment behavior that is not generally accessible. Moreover, many previous studies have been limited by a small sample size; Wilson et al. (2000) use one of the largest samples traced with over 7,000 firms and argue it to be "almost an order of magnitude larger than existing published studies in this area".[9] However, Laitinen and Laitinen (2009) use a sample significantly larger with an estimation sample of some 2,300 firms and a test sample of more than 48,000 firms. Nevertheless, the sample size used in this paper with over 7,000 firms is significantly larger than the average dataset used in prior empirical studies in the field. A large sample better represents the whole corporate population and thus facilitates the building and testing of "generic models" (Wilson et al., 2000).

Finally, the sample has two other unique features; the data comes from a Finnish company's corporate ledger, and the results have implications especially in the construction industry because of the nature of the case company's business. There is neither any published empirical paper traced using ledger data in corporate payment behavior prediction nor any study that predicts payment behavior using a sample of Finnish firms' billing transactions.[10] This is understandable as companies may be reluctant to give their billing information for the use of science. Therefore, the sample of this study has also pioneering significance, as the use of ledger data in corporate failure prediction in past literature is minuscule.

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[9] Altman et al. (1994) use data of over 1000 Italian firms and describe the sample size as "by far the largest of any distressed prediction study to date".

[10] There are a number of Finnish studies investigating the probability of default but no academic research was traced in Finland with a clear focus on the short term profitability of corporate clients (see, for example, Laitinen, 1999, Back, 2005, and Laitinen & Laitinen, 2009). Additionally, Lawrence and Smith (1992) study the use of payment history variables, computed from credit accounts, in loan default prediction in the home mortgages and consumer credit context.

The remainder of this paper is structured as follows: Section 2 reviews the extant literature on the role of credit rating agencies, corporate failure prediction and payment behavior modelling, and describes more closely how this paper differs from the previous studies in the field. Additionally, theory on asymmetric information, relationship lending and information sharing is discussed. Section 3 describes the data, hypotheses, the use of variables and the empirical approach. In Section 4, I present the models developed in this study and their results, which are then discussed further in the concluding Section 5.

2 Literature Review

This study differs from the existing literature in three important ways. Firstly, instead of analyzing the likelihood of bankruptcy or publicly registered default, I create a model that helps identify customers that turn unprofitable even before severe consequences such as registered payment defaults, bankruptcy or reorganization. It is widely known that lenders are likely to be left somewhat empty-handed in the case of a bankruptcy of their borrower; thus identifying troubled payment behavior in advance is vital. Secondly, this study is focused on the construction sector where both the cyclicality of the economy and the lifecycle impact of the business itself have a large effect on the payment behavior of client firms. Finally, I use a unique and confidential business-to-business (hereafter B2B) trade credit customer billing data from one large Finnish company.[11] This enables studying firms' payment history and client firm-creditor firm relationships' length carefully. While prior studies (see, for example, Back, 2005) have used payment disturbances, such as reported failed attempts to collect debt at maturity, in predicting default, this study extends the work of similar studies by providing signs of earlier delinquencies which are not likely to be registered or filed and are consequently hidden from the public. Back (2005) also uses unregistered delays to predict loan default of some 3,000 firms; however, the information of payment delays is gathered by Asiakastieto Ltd's analysts'

[11] Later on referred to as Company X. Company X operates in the construction field but it has clients also from other sectors.

company interviews, thus, no similar level of accuracy compared to real-time ledger data are presented in his study. A customer, whose unpaid bills are failed to be collected, or collected at a very high cost[12], is a true credit risk for a company. The aim of this paper is to predict payment failure using payment history, financial statements and background information, to help the development of credit rating models towards the early identification of a troubled corporate client.

2.1 Literature on the Role of Credit Rating Agencies

External rating services were first introduced in the 19th century in the U.S with the idea that a rating could develop a formal relationship between the borrower and the creditor (Saraç, 2010). Banks adopted internal ratings during the nineties to alleviate loan approval, pricing and monitoring, for instance (Grunert, Norden & Weber, 2005). Hazar and Babuscu (2007) define rating as an instrument that measures the ability and likelihood of a borrower to repay its loan on time and as agreed upon, that is, a borrower's solvency. Saraç (2010) describes credit rating as a more elaborate and institutionalized form of conventional financial analysis process. The rating process "consists of the investigation, evaluation and classification of firms or capital market institutions in terms of organization, liquidity, solvency, profitability and financial structure with the consideration of industrial, economical, political and social conditions" (Official Gazette, 6 March 1997, as cited by Saraç, 2010). A rating provides an objective indicator of each firm seeking capital. Financial institutions and other investors, or in the context of this study Company X, are able to base their credit terms, interest rates, expected returns and other details on these ratings. Risk premiums assigned to each firm are largely affected by their rating scores (Saraç, 2010). Moreover, the use of rating score services has increased since the growing variety of financial instruments (Standard & Poor's Credit Week, 1989). Grunert et al. (2005) suggests that ratings can be interpreted as

[12] See discussion on the dependent variable in Subsection 1.2. Company X defines a client firm that pays at least three of its bills at least 30 days after the due date, within a calendar year, as failed due to fixed collection costs and increased monitoring linked to troubled paying.

a screening technology used to alleviate problems between a borrower and a lender arising from asymmetric information.

The modern theory of financial intermediation explains the need for intermediaries, such as banks, credit rating agencies and advisory financial service providers, by a reduction in costs of asymmetric information (Leland and Pyle, 1977; Diamond, 1984; Bhattacharya and Thakor, 1993). Tang (2006) suggests that rating agencies help to diminish opacity of information in the credit markets through disclosure of new information, thereby influencing firms' access to financing and their investment decisions. The paper shows a drop (increase) in cost of borrowing for firms that were upgraded (downgraded).

The importance of credit ratings has increased in recent years due to growing demand and regulation. Especially banks are faced with higher risk management requirements through Basel II regulations (Basel Committee on Banking Supervision), which oblige that the evaluation of credit risk is based on risk ratings. However, credit ratings are useful tools also in, for example, credit portfolio management of any company. The new legislation has already significantly increased the use of credit scoring by banks (Bofondi & Lotti, 2006). Improvements on the accuracy of credit ratings are important for the prevention of credit crunches arising from an alarming extent of systematic risk. Moreover, some researchers expect a rating to become a prerequisite for obtaining finance in the future (see e.g. Saraç, 2010). On the other hand, the financial crisis of 2008-2010 has damaged the image of rating agencies. As well known, the U.S agencies were overly optimistic in their rating of products linked to subprime mortgages, and again, the financial markets put too much reliance on their ratings' accuracy (See, also, Longstaff, 2010).

Some investors believe that rating agencies are slow to adjust their ratings. Rating agencies have a long term time horizon in their ratings opposite to an investor, or a company, who wishes to receive up-to-date information. (Altman and Rijken, 2004). One solution could be the use of new variables, such as ledger data variables, that are updated daily in addition to the traditional financial variables that are updated on a yearly or quarterly base. In addition to ratings, credit rating agencies appear to have expanded their role from pure information services to monitoring (Boot, Milbourn & Schmeits, 2006; Bannier & Hirsch, 2010). A payment behavior register of recent payment delays, updated using a pool of corporate ledgers, would significantly expand the accuracy of short-term information about the client firms in the pool.

Although all rating agencies put weight to publicly available financial information, rating agencies have different rating scales and thus they may give different scores to the same company (Cantor & Packer, 1997; Bongaerts, Cremers & Goetzmann, 2012). Tabakis and Vinci (2002) suggest that the information credit rating agencies use to create their scoring system can be divided into a core part, based on information publicly available, and a subjective part called an analyst's contribution. The writers show that while the largest U.S. agencies studied in the paper had no significant differences in the predicted default probabilities given a rating, the agencies did display significant differences in their rating of a given set of credit institutions. Thus rating accuracy is not only based on financial information available to all players but also on a specific analyst contribution of knowledge not available to others. If this knowledge is well used, it may well prove to be a significant competitive advantage for a credit rating agency. My model tries to find ways to improve an existing model, used to assign rating scores, with data that updates significantly more often compared to the traditionally used information.

Only a few researchers have focused on studying credit ratings, and a majority of these are implemented with U.S data and focus on the ratings of the three largest rating agencies: Moody's Investor Service, Standard and Poor's and Fitch.[13] I test the prediction ability of both financial and non-financial variables compared to Asiakastieto Ltd's rating scores,

[13] See, for example, Tabakis and Vinci (2002), Tang (2006) and Bongaerts, Cremers & Goetzmann, (2012) for empirical comparison of the largest credit agencies and Saraç (2010) for an analysis of the accuracy of credit analysts' estimates.

to examine possible ways to improve the generic current rating model towards a more interactive approach. Back (2005), Laitinen (1999) and Laitinen and Laitinen (2009) among others have also used data from Asiakastieto Ltd but their studies differ from mine in two ways.

First, the previous work utilizing Asiakastieto Ltd's database predicts primarily severe results of financial difficulties, that is, bankruptcy and restructuring or officially registered payment defaults. Second, the data of these past studies are gathered by the credit analysts of Asiakastieto Ltd mainly from financial statements and thus, for example, problems linked to the time lag between the measurement of the independent and dependent variables are prominent (see, for example, Back, 2005). The data used in my study are daily ledger data from a Finnish company, which enables the measurement of variables with no lag. The only study traced using corporate ledger data is by Hassler, Myers and Seldin (1963). Hassler et al. (1963) build a numerical scoring system to predict later account delinquencies among 600 credit consumer customers of a large Los Angeles department store chain. The reason for the rare use of companies' transaction data in prior literature is that ledger information is often highly confidential and companies are carefully examining the projects they choose to participate in. This thesis is the first study to-date using ledger data to predict payment delays at the corporate level, and one of the few academic contributions to literature on payment behavior prediction.

2.2 Discussion on Corporate Failure Prediction

First, the following chapter discusses the use of financial variables in previous papers in the field. Second, the role of non-financial variables and 'soft' information in credit risk literature is presented. Finally, I analyse prior empirical studies' different definitions of the dependent variable, used to describe the extent and severity of corporate failure.

2.2.1 The Use of Financial Variables in Failure Prediction

Previous studies have widely adopted the use of financial ratios in distress prediction since the pioneering work of Beaver (1966) and Altman (1968). Empirical studies on financial distress prediction have traditionally been based on financial information (see, for example, Zavgren, 1985; Jones, 1987; Laitinen & Kankaanpää, 1999; Jones & Hensher, 2004; Altman & Hotchkiss, 2006; Balcaen & Ooghe, 2006; and Lensberg et al., 2006). However, the reliability and accuracy of financial statements have been under scrutiny especially after cases such as the Enron and WorldCom scandals (Saraç, 2010). The increasing use of accounting loopholes, special purpose vehicles and the lack of transparent financial reporting is making the utilisation of financial statement data less reliable.

Saraç (2010) posits that firms are forced to conceal some of their assets, liabilities or income to reduce tax or other burdens. Furthermore, companies are prone to "window-dressing" despite advanced regulations attempting to abolish it (Saraç, 2010). Nevertheless, financial variables have a stable role in financial distress prediction and their use is widely accepted. Empirical evidence shows that especially financial ratios implying high leverage, inefficiency or poor liquidity increase the probability of bankruptcy (See e.g. Beaver, 1966; Altman, 1968; Gordon, 1971; Altman et al., 1977; Ohlson, 1980; Chen and Shimerda, 1981; Lau, 1987; Gilson, 1989, 1990; Gilbert et al., 1990; Platt and Platt, 1990; Anyane-Ntow, 1991; Chan and Chen, 1991; Flagg, Giroux and Wiggins, 1991; Chen and Lee, 1993; Shumway, 2001; Turetsky and McEwen, 2001). Gilbert et al. (1990) show that cash flow variables have significant explanatory power in insolvency prediction. On the other hand, Ward (1994) finds cash flow variables useful in studying mining, oil and gas industries and suggests that cash flow information is industry specific. Scott (1981), Jones (1987) and Laitinen (1991) add cash flow, firm size and growth to the list of significant variables in terms of both theory and empirical evidence. Other studies find profitability measures such as return on sales to reflect firm longevity (Altman, 1968; Altman et al., 1977; Chen and Shimerda, 1981; Moses and Liao, 1987; Gilbert et al., 1990; Gilson, 1990; Flagg et al., 1991) while others find only weak relation between some profitability variables and financial distress (Turetsky and McEwen, 2001; Saraç, 2010).

Some modern studies question the use of financial ratios due to their unavailability for non-listed firms and announcement only once a year (small firms) or quarterly (listed firms). According to Saraç (2010), the financial statements of small and medium enterprises (SME) cannot be relied on exclusively because they do not reveal all information or reflect it accurately. Additionally, studies such as Altman (1968) posit that the averages of financial ratios shift over time. Naturally the situation of a firm may change rather fast after reporting its financial statements. Thus the predictive power of financial ratios decreases the longer the time lag between the measurement of these variables and the time of the failure.

According to Basel Committee on Banking Supervision (2000), models based on purely financial factors have some disadvantages. Financial factors are mainly backward-looking point-in-time measures so that models based on financial variables are constrained and may not perform out-of-sample (Grunert et al., 2005).[14] Concurrently, as financial factors are measured in the same way by banks and credit agencies, non-financial factors may explain a firm's different rating scores among different intermediaries or creditors (See, also, Grunert et al. (2005). Moreover, a firm may receive a positive response from one lender while a negative one from another due to asymmetric information; a longer client relationship generates valuable information to the creditor (see, also, Berger & Udell, 1995; Sharpe, 1990). Krahner and Weber (2001) define credit rating as a "mixture of mathematical models and management intuition" and underline the essential link between a rating and the likelihood of failure. Nevertheless, weights given to different financial and non-financial factors, and the rating scores separating a poorly performing firm from a financially stable one, are decisions each

[14] Inherently many non-financial variables are subjectively measured and thus similar problems may arise. For instance the limit of late payments that makes a client firm unprofitable is different across companies, industries and time. Additionally, the definition of payment failure may vary across cases. These issues require consideration when applying the results of this study.

rating agency make individually. Although the Basel Committee on Banking Supervision has given a proposal for banks to use their internal credit ratings to calculate regulatory risk weights, these regulations do not have direct implications on the rating system of credit rating agencies.

2.2.2 The Use of Non-financial Variables in Failure Prediction

Only a minority of previous studies relate non-financial variables' role to financial difficulties. Keasey and Watson (1987) use non-financial variables such as audit qualifications, number and change in directors and reporting lags, both alone and together with financial ratios to analyze their role in small firm failure. The writers suggest that non-financial variables have slightly better prediction power compared to traditionally used financial variables. Also Laitinen (1999) finds support for the use of non-financial variables such as payment history and properties of the management in risk scoring estimation. A number of prior studies focus on the use of financial and non-financial variables in testing banks' internal rating system (see, among others, Grunert et al., 2005; Saraç, 2010). Saraç (2010) finds subjective criteria, such as an analyst's own evaluation of shareholders and directors or industry, to be more effective than financial criteria in predicting loan repayment performance. The writer argues that analysts can assess a firm better if they do not rely solely on financial statements. Similar results are reported by Grunert et al. (2005) who study German companies and find qualitative variables such as accounting behavior to help classify companies correctly. Furthermore, Brunner et al. (2000) study qualitative and quantitative ratings and find the former to perform better; for example rating changes derive mostly from the changes in the "soft" sub-ratings, and ratings based on "soft" information show better grades with less dispersion around their means. Also the importance of qualitative information on relationship building has been studied (Berger, Miller, Petersen, Rajan & Stein, 2002; Stein, 2002).

2.2.3 Prior Research on Financial Distress Prediction – The Traditional Definitions of Failure

Financial distress is widely defined as bankruptcy or reorganization (Altman, 1968; Giroux & Wiggins, 1983) whilst financial distress has been thought to stand for business failure (See e.g., Altman, 1968; Altman et al., 1977; Ball & Foster, 1982; Moses & Liao, 1987). Grunert et al. (2005) use the Basel II definition of default as the dependent variable in their study (see Basel Committee on Banking Supervision, 2001).[15] John (1993) defines financial distress as a point in time when the liquid assets of a firm do not sufficiently cover the current requirements of its contracts. However, according to Giroux and Wiggins (1983), bankruptcy is only one event in the financial distress process of a troubled firm. All distress events from decreased cash flows to payment difficulties or bankruptcy reflect firm risk (Turetsky & McEwen, 2001). Additionally, Foster (1986) describes financial distress as a continuum of many points of failure. Other studies such as Pastena and Ruland (1986), Lau (1987), Gilbert et al. (1990), Anyane-Ntow (1991), Johnsen and Melicher (1994), and Ward and Foster (1997) suggest there are numerous heterogonous characteristics for financial difficulties in between the healthy and bankrupt stages of a firm's lifecycle.

The signals of a firm's decline from healthy towards distressed are events such as technical or loan default, reduction in dividend payments or debt restructuring (Giroux and Wiggins, 1983, 1984; Lau, 1987; Flagg et al., 1991; Aksu, 1993; Chen and Lee, 1993). Furthermore, Turetsky and McEwen (2001) suggest that one of the initial signs of a financial distress and failure process is the change from positive to negative in the cash flow from continuing operations. In fact, Gilbert et al. (1990) argues that only a fraction of companies faced with financial difficulties file for bankruptcy. Thus, there may be factors motivating financial distress different from those that are related to bankruptcy. A company may fail to pay its bills on time but never go nearly

[15] The Basel II definition of default is as follows: (i) the bank considers that the obligor is unlikely to pay its credit obligations to the bank in full, without recourse by the bank to actions such as realizing collateral (if held); or (ii) the obligor is past due more than 90 days on any material credit obligation to the bank.

as far as bankrupt. A study that has a narrow definition of failure will fail to capture all events where a client relationship turns unprofitable without the client firm filing for restructuring or bankruptcy, for instance.

2.2.4 Prior Research on Payment Behavior Prediction – The Less Severe Definitions of Failure

Few prior studies predict payment behavior instead of publicly registered business failure; the only academic study traced with a clear focus on future payment behavior prediction at the corporate level is by Wilson, Summers and Hope (2000) with UK data. Wilson et al. (2000) show that payment behavior is more accurate in failure prediction than traditionally used accounting data. Wilson et al. (2000) study the use of payment history (Paydex index) in predicting future payment delays. The writers use payment delays instead of an officially registered payment default as their dependent variable and test two outcomes[16] describing financial difficulties, or payment delays, somewhat similar in the severity of the outcome modeled in this study. The writers show that prior payment behavior has significantly more explanatory power compared to accounting data alone in predicting future payment difficulties and impending failure. Wilson et al. argue that recent payment history not only predicts accurately payment delays but it is also significantly related to looming, more severe, failure. Moreover, the writers suggest that accounting information is less predictive for payment behavior than it is for serious corporate failure as accounting data is infrequent compared to a firm's payment cycle. This thesis focuses on the payment information to find the hidden information that accounting data are unable to capture. Furthermore, in this study, the definition of the dependent variable, as well as the use of ledger data in variable creation and payment failure prediction, differs from any other paper to date.

Whereas occurrence of payment difficulties can be both seen as the first sign of financial troubles (see e.g. Back, 2005), or even a measure of distress in advance of a possible bankruptcy filing

[16] Two outcomes modelled are firms paying on average (1) 15 or more days late or (2) 30 or more days late, for one or more of the next 6 months.

(Ward & Foster, 1997), payment history can also be a sign of a behavioral pattern in which case studying bankruptcy, reorganization or any other public measures of default may not be useful in predicting how profitable or unprofitable a client is to a company, and the likelihood of the business relationship turning unprofitable. A customer that has zero registered defaults in its credit payments or one that never goes bankrupt can still become an unprofitable client due to payment delays and the fixed costs that collection procedures and increased monitoring generate.

I investigate whether publicly available financial information, past registered payment defaults and other background information can be used to predict the likelihood of a client firm failing to pay on time. More importantly, I study whether past late payments are related to future payment failure. Results in this area could be useful to any company with clientele of small enterprises that has no wide access to registered data on for example financial statements or past defaults. In addition to possible collection costs that payments failures generate, payment difficulties or late payments may only be the beginning towards bankruptcy; Turetsky and McEwen (2001) and Wilson et al. (2000) document that failure to pay on time is positively associated with impending failure such as bankruptcy. Moreover, Deloof (2003) studies the working capital management of large Belgian companies and finds that less profitable firms wait longer to pay their bills. On the one hand, it could be that the use of trade credit for a short-term loan is more a last-resort solution for large firms in financial distress rather than a signal of effective management of a successful company, at least in the light of Deloof (2003). On the other hand, companies with strong financial records may be poor payers also for convenience reasons; a late payment can be treated as the use of extended credit to maximize efficient working capital management, or a firm might take advantage over an investment possibility and rather pay interest on late payments than give up that opportunity (see, also, Wilson & Summers, 2000).

2.3 Theory on Informational Problems and Information Sharing

The extant literature analyzes generally the credit decision making of banks and the informational problems of lending (See, among others, Jappelli & Pagano, 1993; 1999; 2000). However, similar problems arise also outside the banking world; companies offering trade credit and intermediaries such as credit rating companies are faced with problems of asymmetric information, moral hazard, adverse selection and agency problems. The following chapter describes the literature around the problems of information and its communication. Although prior literature is mainly focused on the banking industry, similar problems and events take place also in the trade credit context. The chapter proceeds as follows. Firstly, theoretical background on information opacity is presented. Secondly, literature on relationship lending is described. Finally, research on the theory of information sharing is reviewed. Furthermore, I analyze the implications of each theoretical framework on this study.

2.3.1 Asymmetric Information and Cost of Lending – Implications for Credit Risk Management

In case of new clients, assuming no information is shared and no external services used, a company has to base its credit decisions purely on publicly available and sometimes rather old information. Moreover, as discussed earlier, even a firm with strong financials might be a poor payer and thus an unprofitable client. Information asymmetries may lead to a 'lemon's problem', introduced by Akerlof (1970); a seller knows more about a product than the buyer. The theory is applicable to credit markets as well: a lender knows less about a borrower's payment behavior than the borrower. With no information about a new prospective client's payment history, costs of misclassification, that is, Type I and Type II errors, can lead to costly decisions.[17] Moreover, many creditors base their credit decisions

[17] Type I error occurs when failing firms are unintentionally granted credit and Type II error takes place when non-failing firms are inadvertently denied credit (Stein, 2005).

only on the financial health of firms while behavioral patterns are overlooked, partly due to lack of information.

In imperfect markets with asymmetric information, a borrower may have an incentive not to pay on time, assuming that the borrower's past late payments are not severe enough to be publicly registered and the borrower's reputation stays intact. If, however, information about the borrower's payment history is shared among lenders, his reputation is in question and he is more likely not to fail in his payments (see, also, Jappelli and Pagano, 2000). Credit ratings generated from a large pool of corporate ledgers and shared accordingly might significantly reduce information asymmetry and the lemon's problem with new clients and consequently increase liquidity in the credit markets.

2.3.2 Relationship Lending – Implications for Failure Prediction

According to the adverse selection model developed by Pagano and Jappelli (1993), information sharing decreases payment failures and improves the pool of borrowers (See, also, Jappelli & Pagano, 1999, for cross-country evidence). In the model, as in the real world, market players have more information about their long-standing clients than about credit seekers who have newly moved into the market. Creditors are more prone to adverse selection in the case of the latter group; however, exchange of private information by market players helps to mitigate the problem and decrease failure rates.

Berger and Udell (1995) find that longer banking relationships solve problems of asymmetric information and conclude that relationship lending generates valuable information about the quality of borrowers. Sharpe (1990) suggests that longer client relationships allow lenders to benefit from this information asymmetry by capturing "rents" generated by these clients. He also argues that a new client is expected to initially generate losses. A longer relationship reduces the 'hidden' knowledge about a borrower, and this accumulated knowledge over competitors allows the lender to make credit decisions according to all relevant information and gain an advantage over its competitors, that is, gain from information asymmetries in the market.

An interesting question is, in the discourse of these theories, whether client firms with long business relationships with Company X, and a reputation to protect, will in fact fail to pay on time less frequently. Assuming that client relationship age is inversely related to hidden information from Company X, and that it can be used as a proxy for the level of monitoring through client meetings, for instance, clients with longer client firm–creditor firm relations should have better paying habits. Additionally, treating firm age as a proxy for its reputation, older firms should be associated with payment failure less often.[18] On the other hand, it might as well be that smaller firms are monitored more closely due to their assumed higher risk and thus adverse selection might be higher among larger firms.[19]

2.3.3 Theory on Information Sharing – Implications for Future Credit Rating Systems

Jappelli and Pagano (2000) study information sharing in credit markets from banks' perspective and conclude that as all data needed for credit screening and monitoring is not available, banks face adverse selection and moral hazard problems in their lending activity. Adverse selection arises when there is hidden information about borrowers' characteristics, and it can lead to inefficient allocation of credit.

Moral hazard means the opportunistic behavior of a borrower when there is too little monitoring by the lender. Both problems can be mitigated with a requirement of collateral or an equity stake in the project by the borrower. Also a requirement for a borrower's fine reputation helps align a borrower's incentives with those of the creditor; a borrower is more likely to pay on time in the fear of reputation loss. (Jappelli & Pagano, 2000). Equity stakes and collateral requirements

[18] For example Lerner (1994), Gompers (1996), Gompers and Lerner (1999a) and Nahata (2008) have related firm age to experience and reputation.

[19] See Subsection 3.3.2 for discussion on smaller firms' assumed higher risk.

are often not available for many companies offering trade credit; so is the case for Company X. Thus monitoring and close business relationships with customers are even more critical, so is the signalling of a good reputation by a client firm paying on credit.

According to Barnea, Haugen and Senbet (1980), information asymmetries can be reduced through signalling – this is however at a cost. Whereas Ross (1977) argues that in some cases the financial structure of a firm may serve as a signal, Haugen and Senbet (1978) posit that signalling through strong financials is costly. Nevertheless, because of the moral hazard problem, in the absence of a credible signal of a borrower's quality, both lender and borrower carry the agency costs of information asymmetry (Barnea et. al, 1980).

More specifically, Jappelli and Pagano (2000) suggest that exchanging information about borrowers has four positive effects. Firstly, it allows more accurate repayment prediction and eases adverse selection problems. Secondly, it reduces the "information rent" charged from a borrower due to the superior information that the lender has over its competitors. Thirdly, it works as a borrower discipline device by reducing moral hazard as the threat of losing one's reputation with all potential lenders heightens a borrower's incentive to pay on time. Finally, information on the overall indebtedness of borrowers is shared and each borrower's risk of taking too much debt is reduced. (Jappelli & Pagano, 2000). Padilla and Pagano (2000) posit that borrowers' incentive to pay increases especially when the information shared concerns past payment failures. On the other hand, the writers underline that when more detailed information is shared, the result might be opposite.

Based on the positive effects of information sharing, and assuming that ledger data are a successful predictor of payment failure, companies could significantly benefit from the use of a shared pool of payment behavior information deriving from corporate ledgers. If widely accepted and applied, the exchange of private information could reduce the cost of future credit crunches for the entire economy. Competition in the market is necessary, however, to prevent the increased lending to safe borrowers at the expense of more risky borrowers (Jappelli & Pagano, 2000). Additionally, more research is needed in the area to conclude the costs and problems of information sharing.

3 Data, Variables and Methodology

Empirical data and descriptive statistics

The data set consists of both in-house data of one large Finnish company's, Company X's, B2B clients, and Asiakastieto Ltd's data on general, financial, business field and credit information on the same clients firms' identity numbers. The unique transaction data set of 7741 firms, operating in different industry categories, enables a unique empirical analysis of the use of ledger data in payment behavior prediction at the corporate level.[20]

The research follows the payment records of each client firm from January 2010 to May 2012 so that the payment behavior of each client is followed from 1st of January 2010 until 31st of May 2011 and used to predict the possible payment delays during the following year, 1st of June 2011 – 31st of May 2012. The data comprise of billing transactions during two years, though Shumway (2001) argues that hazard models are more accurate and consistent than single-period studies. However, many single period studies have succeeded to contribute to the literature (see, among others, Lawrence & Smith, 1992; Wilson et al., 2000; Back, 2005; Laitinen & Laitinen, 2009). By combining these two data sets, the probability of each firm's likelihood of failing in its payments is analyzed.[21] The empirical study is a snapshot of one specific period of time and thus external

[20] Although the firms in the sample represent different industry categories, they all use Company X's equipment and a majority of client firms operate in the construction sector; thus the sample best represents the Finnish construction market. However, the thesis offers a viewpoint into possible differences in between these industry categories' payment behavior.

[21] Payment failure, defined by Company X, is the dependent variable in the binary logistic regression, and it takes the value of one if a firm pays at least three of its bills at least 30 days after the due date during June 2011 – May 2012, and zero otherwise.

factors such as economic situation in the business field may affect the results.[22]

The following types of information from Asiakastieto Ltd's database are used to predict future payment behavior, that is, payment failure:

1. General information about each client: firm age, past bad credits and defaults on payments, notes of past reorganization or bankruptcy
2. Financial information: liquidity, leverage and profitability measures
3. Business field information: industry category, industry's propensity to default (%)
4. Risk rating information: letter credit ratings by Asiakastieto Ltd

The following information from Company X's database is used to add up to the model. The goal of the research is to study whether these variables can be used to improve the current risk rating model of Asiakastieto Ltd, that is, whether a model adding payment record data of actual clients to Asiakastieto Ltd's data on the same clients, has better explanation power than a model solely based on external financial and background information.

1. General information: date of first purchase by each client, client 'status' information
2. Transaction information: all billing transactions by each client including purchase dates, amount of payments due, amount of payments unpaid, due dates and payment dates of each bill, debt collection letter information

After restricting the data to active[23] B2B client firms only, and after removing the 'VIP' clients, that is, very large client firms with extraordinary collection procedure due to their purchase

[22] Economic cycles in the sectors are captured by a variable describing the risk factor in each firm's business field, or industry propensity to default (%), named 'Industry_risk', measured by Asiakastieto Ltd at the end of 2010.

[23] Client firms that have made purchases within the previous 12 months from May 2012 backwards are considered as active.

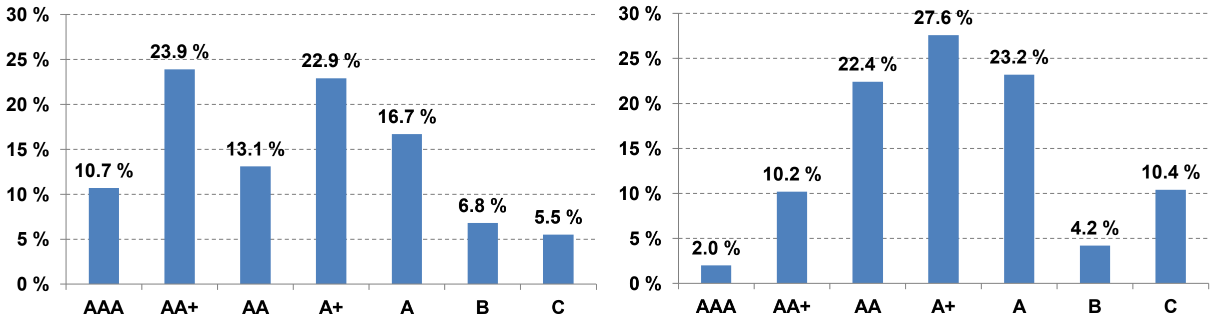
power and thus importance as a client, the data consists of some 197,600 bills from January 2010 to May 2011 and some 225,600 bills from June 2011 to May 2012. The billing data from the first time period are used to calculate the independent variables describing payment history, and the transactions one year later are used to define the possible 'payment failure status' of each firm. In other words, payment delays during January 2010 – May 2011 are used to predict payment failures taking place during the following year.

After deleting duplicates and matching the data used to calculate the independent variables and the dependent variable, the final data were reduced to 7741 client firms: 7512 denoted as non-failed and 229 denoted as failed. This sample is divided into 6123 firms with financial statement data available and 1618 firms that Asiakastieto Ltd has rated but for which financial statement data are missing. I test the prediction power of ledger data variables on two samples separately; a sample consisting of firms with all information available ('reduced sample' with 6123 firms) and a sample that uses both firms with financial statement data missing and firms used in the reduced sample ('whole sample' with 7741 firms). The share of failed firms is some 3.0% in both samples. In order to use a larger sample with a better representation of Company X's clientele, in the final models I use the whole sample to examine the prediction power of payment history variables, and test whether Asiakastieto Ltd's rating score variables can be used to further increase the model's goodness of fit.

Figure 1 Panel 1 presents the distribution of different letter credit ratings among the firms used in the whole sample of this study, and Panel 2 presents the same distribution among Asiakastieto Ltd's firm data base. Company X has relatively less clients with low rating scores compared to the 'public', that is, Asiakastieto Ltd's data base. The lower number of firms with poor rating naturally correlates with the somewhat low number of failed firms in the sample; the small share of failed firms might also be a sign of the credit limit or credit policy that Company X has set for its client firms.

Figure 1: Distribution of letter ratings

Panel 1: Company X´s client firm data base **Panel 2**: Asiakastieto Ltd´s firm data base



The model estimations were made as weighted estimations by giving an equal importance to both failed and non-failed firms. This procedure leads to two equal size groups of failed and non-failed client firms in an attempt to give weights to firms in relation to their misclassification costs; the cost of misclassifying a failed firm is higher than misclassifying a non-failed one (Laitinen, 1999).[24] Similar technique has been used by Laitinen (1999) in his study for Asiakastieto Ltd earlier. Samples with an equal weight on default and non-default firms have also been examined, for example, by Keasey and Watson (1987), Hopwood, McKeown and Mutchler (1989) and Koh & Killough (1990), and this technique is widely used in credit rating modeling. Oversampling of failed firms may lead to biased results; however, this bias is reported to be relatively weak and does neither affect the classification rates nor the statistical inferences (Zmijewski, 1984). It is a subject of further study, at which level the cutoff value in the binary logistic models should be defined to have Type I and Type II errors reflect the true cost of misclassification (See discussion in Chapter 4). However, measuring the true cost of payment failure and the cost of misclassification are out of the scope of this study.

Moreover, I analyze the firms' payment behavior and Company X's credit time allocation over the timeframe of the study. I study whether there is a pattern of Company X granting longer payment times during specific months of the year but I do not find any evidence of such pattern.

[24] The final models use weighted data of some 7741 (5946) failed and some 7741 (5946) non-failed firms for the whole sample tests (reduced sample tests). Some small variation in the sample sizes may appear due to missing values; this variation however does not affect the results.

In addition, I find no significant pattern between the granted payment credit time and the number of days firms paid their bills after the due date: the correlation between the days a bill is paid after the due date, and credit times granted after purchase until the due date, is only -0.056 during January 2010 – May 2011 and -0.087 during the following year June 2011 – May 2012. Likewise, I find only weak correlation between the sums billed and the credit time granted from registration of purchase to due date. Moreover, I find no notable monthly differences within one calendar year in purchases made or in their payment times.

One interesting detail is that firms pay significantly better towards the end of the time period 2010-2012. When restricting the sample to bills not more than 90 days late, no such pattern is visible. It seems that the outliers, extremely late received payments, or payment defaults where payment has possibly never been made, have significantly reduced during the timeframe of this study. The sums of the bills do not show any pattern during a calendar year; purchases are made somewhat independent of the time of the year. Thus I find no evidence that firms would be more likely to pay on time during certain months of the year. This further reinforces my results as it is shown that no external behavioral pattern affects the study that could bias the results. Nevertheless, even though no visible pattern exists where purchases would be made during a certain time of the year, it does seem that firms purchase more towards the end of each month: the data shows a wavy cycle of sums billed growing from the first day of the month until the last day of the month. During some months this pattern is more obvious compared to others.

The billing data consists of both bills that have been paid, either on time or after the due date, and bills that were still unpaid in May 2012. The average (median) time firms took to pay their bills after the due date is 5.37 (1.00) days for January 2010 – May 2011 and 4.03 (1.00) days for June 2011 – May 2012, the difference being statistically significant at the 1% level. This difference is likely due to the notable decrease in the extremely late payments and defaults towards the end of the timeframe. However, the credit time granted to firms from registration of purchase to due date has also grown: this time is on average 16.80 days during January 2010 – May 2011 and 20.89 days one year later, the difference being significant at the 1% level. The median credit times granted, from purchase until the due date, for both timeframes is 15.00 days. Naturally more credit time should decrease the likelihood of delinquency. However, as discussed earlier, in this sample, credit time granted in days since purchase until the due date of the bill, seems to have very weak influence on payment behavior.

During January 2010 – May 2011 (June 2011 – May 2012), 83.85% (86.37%) of bills were paid on time, that is, before a reminder bill would be sent eight days after the due date. 12.94% (11.41%) of bills were paid 8-29 days late and 3.21% (2.22%) were paid at least 30 days after the due date. The average sum of bills paid on time is 452.58 (844.53) euro while the average is 531.03 (1,037.30) euro for 8-29 days late payments and 1,034.53 (1,667.18) euro for bills paid at least 30 days after due date. It would seem that, on average, smaller bills are paid better than larger ones. On the other hand, it might be that firms that purchase with larger amounts pay late more often. Medians of purchases made are 172.20 euro for January 2010 – May 2011 and 223.25 euro for June 2011 – May 2012.

Models

Seven models are tested using different independent and dependent variables. The independent variables are used to develop models consisting of: (1) financial and background variables; (2) ledger data variables; (3) credit rating scores and (4) different combinations of (1), (2) and (3). The dependent variable used is a payment failure event described earlier; (a) a firm paying at least three of its bills at least 30 days after the due date during June 2011 – May 2012 is denoted as failed, and consequently the dependent variable takes the value of one (1). In other cases, the dependent variable takes the value of zero (0). The seven models are the combinations of each set of dependent and independent variables from (1)-(3) and (a). These models and their prediction abilities are tested and compared, and their classification accuracies are shown in Model 1 through Model 6. The dependent variable is measured in all cases from Company X's ledger data but the combination of the independent variables varies in different Models 1-6.[25]

3.1 The Choice of Model

Different methods used in prior literature of failure prediction are discriminant analysis (DA) or linear discriminant analysis (LDA), linear regression (OLS) and logistic regression (LR). Other techniques used are neutral networks (NN) and classification trees (CT). A large number of previous empirical studies since Altman (1968) have attempted to create different indices of failure proneness (z-score, using discriminant analysis). (Wilson et al., 2000). While the use of discriminant analysis has been criticized widely, logit, probit and multilogit estimators have avoided some of the problems (see, for example, Aldrich & Nelson, 1984; Lo, 1986; Wilson et al., 2000). Desai, Crook and Overstreet (1996) and Arminger, Enache and Bonne (1997) compare the models' prediction power and find both LR and NN the most accurate in failure modeling in terms of overall performance. On the other hand, Lee, Chiu, Lu and Chen (2002) find no significant difference between the classification rates of the models.

Allen et al. (2004) suggests four different methods most suitable in identifying variables that have statistical explanatory power in predicting default; 1) the linear probability model, 2) the logit model, 3) the probit model, and 4) the multiple discriminant analysis model. Laitinen and Kankaanpää (1999) test six alternative methods' (LDA, LR, RPA, NN, HIP and survival analysis) prediction power in failure prediction with financial ratios and although no superior method was found, results show that logistic analysis yield the highest prognostic accuracy with 89.5%. Also several other studies stand for logistic regression due to its accuracy in empirical models (see Lawrence & Arshadi, 1995; Thomas, 2000; Kocenda & Vojtek, 2009). Laitinen and Laitinen (2009) use the logistic model, as majority of financial variables are not normally distributed and therefore the use of some other models could bias the results. On the other hand, some writers see this as the con of the logistic model; the fact that logistic regression

[25] Model 7 is further discussed in Section 4.3.

does not assume a liner relation between the independent and the dependent variables has been criticized. Nevertheless, there is evidence that a majority of credit scoring datasets work well with the logistic model as they show only weak linearity (Chen and Huang, 2003).

Wood and Piesse (1987) suggest that a model's ability to discriminate ex ante between failure and survival is showing its true usefulness instead of differentiating between the two ex post. Unlike in some prior studies such as Gilbert et al. (1990), my data are not an ex post selected set of failed and healthy firms. Instead, I observe firms ex ante and follow their possible succession in paying their bills on time during January 2010 – May 2011, and their tendency towards payment failure during June 2011 – May 2012. Similar technique has been used by Turetsky and McEwen (2001). Naturally not setting the number of failed firms fixed before deriving the data leads to a higher rate in healthy companies which gives a more realistic image of the general population. This is also prominent in my data; 2.96% of the firms followed through 2010-2012 are considered as failed while rest of the client firms are considered as profitable clients (non-failed) for Company X – at least during the timeframe of this study.

3.2 Limitations of the Study

The unique data has both pros and cons. On the one hand, it offers a close view on one large Finnish company's B2B clientele's behavior; on the other hand, it represents only a small fraction of the Finnish B2B construction market and thus the results' application to other business areas needs more research before any strict conclusions can be made.

Right censoring

The unique approach to the definition of the dependent variable by Company X, payment failure, restricts the use of the results without further research. The most important limitation is the definition of the dependent variable, and its measurement. There are several clients in the data set that do not fall in the category of a failed firm but still pay very poorly. On the other hand, even a failed firm might have a significant change in its financial situation after the timeframe of the study. The definition of payment failure is also applicable to Company X only; another company may find an unprofitable, failed, client of this study yet a profitable one, or vice versa, find a client unprofitable even after one long payment delay. The definition of an unprofitable client is very industry dependent as well. In some other industry where purchases are made very often, only three late payments are easily covered by tens or hundreds of prompt payments by the same client.

Due to the rather different roles that different construction goods have in a project's lifecycle, it is a known fact among the players that their customers are more prone to paying on time at the beginning of a construction project's lifecycle, and more likely to have difficulties at the end of the lifecycle, as the start-up capital tends to have run out and profits are still awaited. Companies are often specialized on different parts of a construction project lifecycle with their products. Companies that sell, rent or produce goods that are used at the beginning of a project, are more likely to be paid on time both for reasons linked to the finances of the customer and the fact that customers often wish to keep their relationships strong especially to companies that offer services that are crucial for the smooth beginning of a project. A pool of companies with a similar and overlapping customer base could significantly benefit from sharing of private information concerning early signs of payment difficulties by their shared clients. However, the fact that Company X profits from its role in the beginning of the product lifecycle in the construction field, may lead to the share of failed client firms to be relatively smaller for Company X compared to other players in the sector. Thus, the results of this study should be carefully applied especially when dealing with business sectors very different from the construction business. Nevertheless, it can be assumed that a client firm with more than three severe payment delays within a year is likely to cause some troubles for its creditors and other companies that it is in a business relationship with, also outside the construction field.

Selection and survival bias

Selection bias might be present in this thesis, although it is not expected to have great effect on the results. The data comprises of only client companies that are already in a business relationship with Company X and have made payments during the past 12 months. Thus firms that have not appeared sufficiently creditworthy, or have for example severe prior payment defaults, are most likely denied credit and thus left outside of the sample already at the beginning. Selection bias in the loan approval process, or client credit approval in the context of this study, could bias the weights in the scoring model estimate (Mester, 1997). According to Banasik, Crook and Thomas (2003) such models can be presumed unimpaired only if the "accepted" sample firms' behavior is identical to those "rejected". Nevertheless, regardless of whether a model may be presumed to govern all firms, the model can be used to more accurately predict the subsequent payment performance (Basanik et al, 2003). Additionally, Basanik et al. (2003) find that the difference between the accepted and rejected groups is only small.

Moreover, the purpose of this study is to analyze an existing client firm's probability to fail in its payments, thus, Company X is interested in the possible qualities of a failed firm that the company might have overlooked so far when making its credit decisions. The goal of the thesis is not to predict the likelihood of payment failure for a randomly chosen firm, but to predict the probability of failure for Company X's existing clientele. As my models attempt to capture the future payment performance of existing clients, selection bias is an irrelevant problem in this study. As for new clients, the model as it is cannot be used. The model can be run only after some payment behavior data has accumulated in the company's ledger. In spite of this, financial and background variables are robust also in case of new clients: ledger variable models are expected to work best when used as the extension of Asiakastieto Ltd's current model that offers longer inspection interval compared to day-to-day ledger data.

Survival bias could be present as some of the firms might turn into unprofitable clients, or some of the bills might be paid, after the timeframe of this study. To prevent survival bias, all bills are treated equally regardless of whether they have been paid by the end of the timeframe; only the number of days a bill was paid after its due date, or the number of days a bill is still late at the end of May 2012, are considered. Company X did not define any certain limit of days after which a bill would be considered permanently defaulted. From the data it is visible that some payments have been received even more than a year late, which is probably not uncommon for this type of industry where projects can be delayed and profits can be realized only after months or years. Moreover, the purpose of this paper is to study somewhat short-term changes and patterns in behavior, visible in daily ledger transactions during some two years. Thus I leave the analysis of long-term behavioral patterns for future research.

Moreover, for example, a late payment of a 500-euro bill is not directly comparable to a late payment of a 15,000-euro bill. However, the assumption of this study is that the collection and monitoring costs due to payment failure, make a firm an unprofitable client after the limit of at least three at least 30 days late payments by the client firm, regardless of the sums in question. It is also very likely that a firm that pays its bills late this often will continue to do so in the future. As discussed earlier, the definition of failure is subject to Company X's business characteristics and the company's own analysis of its client firms' profitability. In summary of the limitations of this study, the results discussed in Chapters 4 and 5 should be carefully examined when applying outside the construction industry.

Naturally the sample restricts the wide use of the results before more research is available of the use of ledger data in corporate failure prediction, using a sample of randomly chosen firms from all industries. However, although the definition of the dependent variable is company-related, the thesis is expected to provide useful evidence on the use of ledger data in payment behavior prediction. If ledger information prove to have significant prediction power in the models developed in this study, the use of ledger variables is justifiable in other industries as well.

3.3 Descriptions of Independent Variables and Hypotheses

I use four different types of independent variables to predict payment failure: (1) financial variables; (2) non-financial background variables including general information of each firm, industry variables and past registered financial difficulties or payment disturbances; (3) payment behavior and other variables computed from ledger data; and (4) Asiakastieto Ltd's letter rating scores, named Rating Alfa.

3.3.1 Financial Variables

According to Laitinen and Laitinen (2009), independent variables should be chosen for their relation to the symptoms of financial distress. Because the dependent variable in this study is different from prior research, I expect ledger information describing past history to best predict the payment failures one year later. In addition, however, I study whether payment failure is related to weak financials to analyze the possible reasons behind poor payment habits. Laitinen and Laitinen (2009) use six independent financial variables in payment default prediction; size is measured by logarithm of net sales, growth by percentage change in net sales, profitability by return on investment ratio, liquidity by the quick ratio, cash flow by the relation of operating cash flow to net sales, and leverage by the equity ratio based on book value of assets. Previous literature supports the use of these financial dimensions (see, Scott, 1981; Jones, 1987; Laitinen, 1991, and the discussion in Chapter 2). Laitinen and Laitinen (2009) show that size, liquidity and low leverage are negatively related to default while the relation is positive for growth of net sales.

The sample consisting of firms with financial statement information available, the reduced sample, is used to test the prediction ability of financial data gathered by Asiakastieto Ltd at the end of 2010. After some preliminary tests, I restrict the number of variables to those that significantly add information to the model. I use current ratio to describe liquidity, equity ratio to take account of leverage and a dummy variable named 'Operating_profit_dummy' to describe whether a firm has generated a positive (0) or a negative (1) operating profit. This variable considers the profitability dimension. All variable descriptions and their formulas are presented in Appendix 1, Table II.

Richardson, Kane and Lobingier (1998) study the effect of economic recession on corporate failure prediction. The writers find that the prediction power of financial variables might be affected by economic downturn; however especially current ratio and leverage measures perform well during a downturn period. As this study uses data from 2010 – 2012, the ongoing sovereign debt crisis and its effects on Finnish economy might affect the power of the models. Naturally the sample might be skewed due to the sensitiveness of construction business to economic turbulence. To avoid this, the financial variables used in this study reflect leverage (equity ratio) and liquidity (current ratio). Moreover, in Finland, equity ratio has been proved to be a "superior single predictor of payment default" (Laitinen and Laitinen, 2009; see, also, Laitinen, 1999; 2005).

3.3.2 Non-Financial Variables

Non-financial variables are somewhat a new subject of research in the failure prediction literature. Keasey and Watson (1987) show that the number of directors and submission lags are accurate in financial distress prediction. Laitinen (1999) use both publicly registered and unofficially registered payment delays in his study and shows that payment history and characteristics of directors are important predictors of the risk assessment scores made by financial analysts. Back (2005) studies characteristics of management, prior payment behavior, group membership and age in failure prediction and finds support on Laitinen's (1999) results. Additionally to payment history, both the age of a firm and industry variables are shown to possess predictive power also in other studies such as El Hennawy and Morris (1983) and Shumway (2001).

Laitinen and Laitinen (2009) use measures such as firm age, industry, submission lag, characteristics of directors, and company legal form to predict registered payment default. The paper finds empirical evidence that number of board members decrease the likelihood of a default while industry propensity to default (%), number of board members' links to default firms or their own personal defaults, significantly increase the probability of failure. The paper also documents that default firms are significantly younger compared to non-default firms. Hyytinen and Pajarinen (2008) study credit rating disagreements due to asymmetric information and argue that young SMEs are informationally opaque. Asymmetric information could explain the higher likelihood of younger firms defaulting in their payments as lenders have less credible information as a basis for credit decisions; private internal information accumulated during the client relationship becomes even more important.

General information. Independent variables belonging to this group are a customer firm's age in years since foundation and the size of its balance sheet. As in prior research, I use the natural logarithm of total assets as a proxy for size. Age is measured in years since the registration of the firm. Prior studies suggest that size of a distressed firm is positively related to its survival as larger firms tend to better manage adversity (Thompson, 1976; Altman et al., 1977; Ohlson, 1980; Chen and Lee, 1993; Audretsch and Mahmood, 1995). Age of a firm is usually treated as a proxy for reputation, connections and stability of business. Laitinen (1999), and Laitinen and Laitinen (2009) show that older firms are less likely to default in their payments. Chen and Lee (1993) find that firm age and size correlate strongly implying that age could be used as a proxy for size. Size and credit risk are usually shown to be inversely related (Laitinen, 1999); smaller firms are riskier as they are often younger and their balance sheets and cash flows might not be strong enough to overcome financial distress. As this thesis measures the likelihood of payment failure, instead of an official default, it will be interesting to see whether larger firms in my sample fail less frequently – or whether some of the firms seem to fail for reasons other than poor financials or approaching financial distress.

Industry variables. Industry variable 'Industry_risk' is used to control for the firms' business fields' and markets' economic situation and it measures the share of firms with reported payment disturbances during the past 12 months. Thus, Industry_risk describes the firms' industry categories' propensity to default (%), reported by Asiakastieto Ltd at the end of year 2010. Financial statement data and background information were gathered from Asiakastieto Ltd's database and they describe each firm's characteristics at the end of year 2010. The industrial classification of the firms is presented in Appendix I, Table I. Six industry specifications were used as an independent categorical variable, as shown in Table II: (TOL1) manufacturing, (TOL2) transportation and storage, (TOL3) professional, scientific and technical activities, (TOL4) administrative and support service activities, (TOL5) wholesale and retail trade; repair of motor vehicles and motorcycles, and (TOL6) construction. The rest of the business fields are described as (TOL7) others. 'Others' was used as the comparison group in the categorical variable named "TOL", that describes the industrial categories of firms, so that, for example TOL1 (TOL6) describes the higher likelihood of payment failure that firms operating in manufacturing business (construction business) have, compared to firms operating in other industries present in the sample.

Registered financial difficulties or payment disturbances. Laitinen (1999) uses payment history variables such as the number of publicly registered bad debts to predict analysts' credit risk estimates with good results. In my study, variable 'Past_default_dummy' takes the value of one (1) if any of the following is different from zero; number of past registered defaults, number of past registered bankruptcy applications, number of past restructuring applications or number of past reminders of last resort before collection, and zero (0) otherwise.

3.3.3 Ledger Data Variables

In addition to past payment variables, Company X's ledger data are used to identify client firms better; length of client relationship with Company X, and Company X's category of the customers' importance to the company, are used as background information. Length of the client relationship is measured in years since first purchase. Clients with 'abnormally' high client importance status are removed from the data not to bias the results. These clients with 'VIP' treatment are often large publicly listed companies that are not deemed unprofitable or failed regardless of their payment behavior. Nevertheless, large firms subject to normal collection process are a part of this study and thus the impact of size is of empirical interest.

Payment history is the only independent variable that is able to capture the firms' situation very close to the time period when the dependent variable is measured. Laitinen (1999) finds the logarithmic number of recent serious and systematic delays in payments (unofficially registered by main creditors) to significantly increase the credit risk estimate of a firm. Wilson et. al. (2000) successfully model future payment behavior with using a payment index as their independent variable. In addition, prior research has used payment history also in failure prediction; Lawrence and Smith (1992) study loan defaults and delinquencies in mobile home industry and find payment history, measured by most recent delinquency status and frequencies of 30-day and 60-day delinquencies during the previous year, to be paramount in loan default prediction.

H1: Variables calculated from the ledger data moderates other information needed in future payment behavior prediction.

Back (2005) finds that non-financial variables show potential tendencies towards financial difficulties earlier than financial variables. Payment transaction data offers the most up-to-date information about each client firm's probability to fail in its payments. Payment behavior variables have also other pros; payment failure might either be an indicator of financial difficulties or a behavioral pattern that a firm has in its transactions. Financial difficulties may be temporary but often lead to a series of events. Payment disturbances can also affect a firm's reputation and worsen the wicked cycle. Payment delays can weaken a firm's creditors' confidence in the company, cease its future credits or increase its interest rates, and thus decrease its investments leading to even more difficulties. (See, also, Back, 2005). On the other hand, payment failure might be a sign of a firm's misuse of its purchase power and thus client status; payment delays might also signal the use of trade credit as extended credit (Wilson & Summers, 2000). If the reasons behind payment failure are not linked to financial troubles, it is possible that one explanation can be found looking at working capital management. Whether payment failure is related to financial difficulties or payment habits, real-time ledger data offers the most recent information about a client firm's payment delays.

This paper's use of variables describing past payment behavior is similar to Back (2005), who shows that previous payment delays significantly increase the probability of bankruptcy and reorganization. Back (2005) argues that payment delays might be the beginning of a permanent payment default. This conclusion supports the importance of identifying client firms with payment disturbances early enough. A company might find justifiable to end its business relationship to a client firm with regular late payments before the relationship's profitability turns negative.

The main variables computed from Company X's ledger data, describing past payment behavior, are the natural logarithm of number of delayed payments measured during January 2010 – May 2011. The variables have been divided into two groups depending on the number of days a payment has been paid, or is still in May 2012, late; 8-29 days and 30 or more days. The company sends a reminder bill only after a delay of eight days due to banks' transaction lags and possible effects of weekends and public holidays. The first variable named 'late8-29' is the natural logarithm of number of bills paid 8-29 days after the due date, divided by the natural logarithm of total assets in 2010. The second variable, 'late30+', is the natural logarithm of number of bills paid at least 30 days after the due date, divided by the natural logarithm of total assets in 2010.

A large firm probably generates more accounts payable, in absolute terms, compared to a small firm, independent of its financial situation. Moreover, larger firms tend to purchase more often and, other things equal, also pay late a larger absolute number of their bills even if the relative amount of late payments would be equal to that of smaller firms. Large firms may also misuse their purchase power and importance as a client and delay their payments for convenience reasons. To take account of this, I compute all ledger variables in relation to each firm's size; dividing the number of late payments by total assets eliminates the possible size bias by making the variables relative to a firm's purchase power.[26]

In addition, two other ledger variables are computed to test the robust use of ledger information; 'RelativeLate' is the total number of payments made at least eight days after the due date during January 2010 – May 2011, divided by the total number of purchases made during the same period, by the same firm. 'RelativeLate30+' describes the number of bills paid at least 30 days after the due date, divided by the number of all bills paid at least eight days after the due date.

Additionally to payment history, Company X's information includes the length of each client firm's business relationship with the company. Wilner (2000) argues that longer client firm–creditor firm relationships induce dependent creditors to grant more debt concessions when the debt is renegotiated, compared to non-dependent creditors. The more concession a borrower receives, the lower should be the probability of payments difficulties. A longer client relationship also accumulates knowledge and reduces informational asymmetries which make credit decisions easier for the creditor company (See also the discussion in Subsection 2.3.2).

H2: The longer the client relationship, the less likely the client firm is to fail in its payments.

[26] In addition to total assets, the effect of size has been tested using other proxies of size in the denominator for past payment behavior variables: net sales in 2010 and total purchases made during January 2010 – May 2011 were also used in preliminary testing. The results are robust and support the results gained with variables described in this study.

3.4 Combined Information

Financial and non-financial as well as payment behavior variables correlate to some extent and may include overlapping information, thus diminishing each other's effects. To prevent multicollinearity, variables have been selected to avoid introducing highly correlated variables to the model concurrently.[27] Correlation matrixes are presented in Appendix III. Nevertheless, a model using combined information is usually expected to outperform models based on financial or non-financial variables alone in terms of binary classification and fit (see, Keasey & Watson, 1987).

H3: The models based on combinations of internal and external data outperform models using only internal or only external data.

However, in this study, the financial variables measured at the end of year 2010 are expected to have significantly lower prediction power on payment failure taking place during June 2011 – May 2012 compared to payment history variables measured during January 2010 – May 2011. This expectation is based on both the longer time lag between the measurement of the financial variables and the dependent variable, and the fact that payments delays will not in all cases yield from financial distress or lead to financial default, in which case financial variables are expected to be ineffective. The effect of combining payment behavior information with financial and non-financial background information is left as an empirical question rather than a hypothesis. The hypotheses concerning models using combined information should be subject to the combination of variables used in the empirical study, as noted by Laitinen and Laitinen (2009).

H4: Variables calculated from the ledger data offer additional information over and above traditionally used financial and non-financial information in payment failure prediction.

[27] Farrar and Glauber (1967) conclude that multicollinearity is not likely to affect results as long as correlation between variables is below 0.8. Moreover, the highest correlation in the models occurs between categorical variables' different categories. No other highly correlating variables are introduced to a model concurrently.

In addition to financial and non-financial separately chosen variables, I test whether Asiakastieto Ltd's letter rating scores assigned at the end of 2010, named Rating Alfa, add information to a model using primarily only ledger data. Rating scores are a complex mixture of financial, non-financial and payment history variables gathered from external sources such as financial statements, public registries and also a pool of other companies ledger data, not linked to Company X. Rating Alfa estimates a firm's probability of facing financial difficulties or bankruptcy within the next 3 years following assignment. As the ratings do not measure the exact same event as the definition of payment failure in this paper describes, it is expected that Company X's own ledger data offer more up-to-date and accurate information over and above current rating scores. However, it is hypothesized in H3 that the combination of these two information sources together work better at predicting future payment behavior than ledger data do alone.

H5: A company's own ledger data variables are the most significant predictors of payment failure, even compared to rating scores that use a pool of other companies' ledger data with financial and background variables.

4 Results

Firstly, the following chapter presents the descriptive statistics, and secondly results from the binary logistic models are analyzed. In the Models 1 through 4 I first use the weighted reduced sample of firms with financial statement information available to study the prediction power of traditionally used financial and somewhat newly introduced non-financial background variables. Second, I compare the results from Model 1 to Model 2a that utilizes primarily only ledger data, and examine whether ledger variables have higher prediction power compared to external information used in Model 1. Thirdly, I study whether Models 3 and 4 using combinations of external and internal data outperform models that use only internal or only external information. Finally, I use the whole sample, that includes both firms for which financial statements are not available and firms of the reduced sample, of Model 5 to test the accuracy of ledger data in payment failure prediction. In Model 6 utilizing the whole sample, I use Rating Alfa as an independent variable in addition to ledger data variables.

The seven letter ratings describe the risk estimate of each firm so that AAA denotes the highest rating and C denotes the poorest rating, respectively. Rating score C has been used as the comparison group in the models so that each coefficient of a letter rating AAA–B in the model denotes the lower risk of a firm with that rating, compared to the firms with the rating ‘C’. As rating scores are created to measure the long-term credit worthiness of a firm, it is expected that the scores of 2010 should also be able to predict payment failures during June 2011 – May 2012 somewhat precisely. All variable descriptions and their formulas are presented in Appendix 1, Table II.

Comparison of means

T-tests of differences in means between failed and non-failed firms are presented in Table III. Test statistics show that the firms differ from each other significantly with respect to age, size, current ratio, equity ratio, operating profit, past default history and payment habits. Also the firms’ industry categories’ propensity to default (%) seems to be on average higher for failed firms, the difference being statistically significant at the 1% level. The average age for a failed firm is 15.96 years while it is 18.59 years for firms that are more likely to pay their bills on time. The average sizes of the balance sheet for a failed and a non-failed firm are 68.27 and 18.33 million euro, respectively.[28] The result supports the earlier discussion that larger firms may take advantage of their purchase power and pay late for convenience reasons. On the other hand, Deloof (2003) studies large Belgian firms and concludes that less profitable firms wait longer

[28] As discussed in Subsection 3.3.3 in more detail, to account for the significant influence of size, and to consider the potential bias of larger firms making more purchases and thus paying a larger number of bills late, ledger data variables describing past payment behavior have been divided with size thus neutralizing the possible bias effect.

to pay their bills. Thus, it is left for future research to analyze, whether large companies with financial troubles affect the results more than their non-failed peers, or whether large firms for example use trade credit as extended credit and fail because of convenience reasons.

Non-failed firms have been in a business relationship with Company X on average for 6.33 years while failed firms have been clients on average for 6.12 years. The difference is not significant, however, probably due to the somewhat small number of failed firms in the unweighted sample. Also higher liquidity, measured by current ratio, and stronger balance sheet, described with equity ratio, seems to be associated with good paying habits more often: current ratio is on average 2.68 (1.40) and equity ratio 35.74% (18.59%) for non-failed firms (failed firms). The medians give further support to the results; for example, while median values of variables describing past payment delays are zeros for non-failed firms, the values are positive for failed firms. All figures are presented in Appendix 1, Table III, in more detail.

4.1 Models Using the Reduced Sample

Models based on financial and non-financial information

Model 1, Panel 1 through 3, in Appendix 2, present the results for the binary logistic regression model predicting payment failure on the basis of eight financial and background variables that proved most significant in the preliminary tests. Panel 1 shows the model summary tests. The Nagelkerke R-Square (a modified version of the Cox & Snell R-square) for the model is 0.245. The most significant parameter is the ln(size), measured by the natural logarithm of total assets, with a Wald statistic of 983.9. However, also the natural logarithm of age, current ratio, categorical industry variable TOL, and the industry categories' propensity to default (%), 'Industry_risk', have somewhat high Wald statistics even though size clearly dominates the information in the model. All eight variables are significant at the 1% confidence level. The model classifies correctly 67.1% of non-failed firms and 72.2% of failed firms.

In summary, the probability of payment failure is significantly increased with size, negative operating profit, level of risk in the firm's industry, and existence of past registered financial troubles. On the other hand, age, current ratio and equity ratio seem to reduce the likelihood of payment failure. Client firms operating in (TOL6) construction, (TOL3) professional, scientific and technical activities, (TOL4) administrative and support service activities, (TOL5) wholesale and retail trade; repair of motor vehicles and motorcycles, (TOL2) transportation and storage, and (TOL1) manufacturing are associated with failure more often compared to other industries, so that TOL6, construction, shows the highest risk towards payment failure, whereas TOL1, manufacturing, shows the lowest risk, respectively. Appendix I, Table I, presents the industrial classification of firms and their respective shares of failed and non-failed firms.

The results concerning the influence of age, leverage, liquidity and past signs of financial distress on the likelihood of payment failure, support earlier evidence reported by Laitinen and Laitinen (2009) among others. Again, the effect of size and age are supported by theory presented in Subsection 2.3.2; older firms on are more likely to have more established business, larger funds and a reputation to protect which all make these firms better payers; larger firms are more likely to have an opportunity to misuse their purchase power and may pay late due to reasons other than financial troubles. On the other hand, the business relationship with Company X might be crucial for some of the smaller firms in which case reputation as a prompt payer is important for business continuation.

Since the definition of payment failure is company-related to some extent, the background of Company X's clientele must be considered. The following analysis is not based on discussions with Company X. Firstly, it could be that a firm that makes large purchases on a regular basis brings more revenue to the company compared to a smaller firm; following its purchase power, a large firm might be approved trade credit more easily than a small firm. This could lead to a large firm receiving credit even with weaker financials compared to a small firm only because a large firm is nonetheless seen as a less risky choice due to reasons such as a larger balance sheet, monitoring backed by several creditors, better reputation and, naturally, ability to generate more cash flow to the creditor-company. If larger firms are given credit on easier terms and "second chances" more often, even after some payment disturbances, large firms might be attempted to delay payments. Smaller firms, which are followed much more closely both preceding and following a positive credit decision, have a higher incentive to protect their reputation, especially as small firms are often new entrants in the market. The evidence supports this conclusion; size of a firm has a positive effect on the likelihood of payment failure. This result contradicts the evidence in majority of prior studies (see, among others, Scott, 1981; Jones, 1987; Laitinen & Laitinen, 2009). However, the evidence does not necessarily mean that larger firms are riskier per se but that they might have been granted credit more easily in the first place.

Secondly, larger firms may misuse their client relationship status; a large client is important for a company and thus its poor payment behavior might be overlooked. Larger firms also gain from 'economies of scale' as they are more likely to have investment activity that yields returns higher than the interest rate paid for late payments – the opportunity cost of paying on time might just be too high. This result implicates that the use of trade credit as extended credit could explain at least a fraction of the payment delays (see Wilson & Summers, 2000). The above is also the reason for restricting the sample only to firms with normal collection procedure; as stated earlier, clients with a 'VIP' treatment are not part of this study.

Models based on ledger data

Model 2a presents the results for the logistic regression model based on the ledger data received from Company X. Panel 1 shows that the -2 Log likelihood test and pseudo R-squares for the model using ledger data are better than those for Model 1 using financial and non-financial variables. The Nagelkerke R-square is 0.505 and the overall classification 79.3%. Panel 2a also shows that the Wald statistic values are on average significantly higher for variables describing past payment behavior compared to the Wald statistics of the variables based on financial and background information. The payment behavior variables 'late8-29' and 'late30+' have Wald statistics of 1468.5 and 516.0, respectively. Past payment history clearly is a dominating factor when predicting payment failure.

Laitinen (1999) shows that the logarithmic number of recent serious and systematic delays in payments significantly increases a corporate analyst's risk estimate of the firm in question. My evidence supports his findings: the risk of a client firm failing in its payments is significantly increased with payment delays, independent of the number of days a bill has been late.[29] Moreover, my results show that the natural logarithm of number of bills paid either 8-29 or at least 30 days after the due date, divided by the natural logarithm of total assets, are accurate predictors of payment failure independent of the denominator; all variables using total assets, net sales and number of total purchases as a denominator are significant. Different denominators are used to test the variables' robustness: ledger data has economically significant prediction power even when different measures of the client firms' size, and thus purchasing power, are used.[30]

I also test the use of two different ledger variables in Model 2b; variable 'RelativeLate' describes the number of bills paid at least eight days after the due date, divided by total number of purchases by the same firm. Variable 'RelativeLate30+' describes the number of bills paid at least 30 days late, divided by the number of all bills paid at least eight days late. Also these variables are significant predictors of payment failure, adding robustness to the use of ledger data in failure prediction. However, Model 2a overperforms Model 2b in terms of goodness of fit, measured by R squared, and firms' accurate classification; consequently, the ledger variables presented in Model 2a are used in the final models. Nevertheless, the results are consistent with the first hypothesis, H1, presented in Subsection 3.3.3: ledger data variables are accurate predictors of payment failure, even when used in a model without financial variables.

The length of the client relationship with Company X is inversely related to the probability

[29] Company X sends the first reminder note only eight days after the due date. The eight days are used to account for public holidays, weekends and different lengths of payment transactions by banks.

[30] All different variables tested are not presented in this thesis. However, all the results are available upon request.

of payment failure. The result is consistent with the theory on information asymmetry and relationship lending presented in Chapter 2 and H2 presented in Subsection 3.3.3; a more established relationship gives the creditor superior knowledge of that client firm, which helps the credit decision-making process. In addition, lenders are prone to ease the terms of credit with better-known and trusted clients. (Berger & Udell, 1995; Wilner, 2000; Sharpe, 1990). Moreover, client firm age has a negative relation with the likelihood of failure, as in the previous models, giving support to prior research linking longer age to better reputation and more established business (See discussion in Chapter 2).

Models based on combined information

Model 3 presents a model combining ledger data variables to selected financial and non-financial background variables. This model seems to predict payment failure the most accurately: the model classifies 83.6% of non-failed and 77.8% of failed firms correctly. The Nagelkerke R-Square is the highest so far with the value of 0.544. Also the –2 Log likelihood and the pseudo R-squares continue to improve from the previous models. Perhaps the only problem with Model 3 is the dominance of the ledger variables; ledger data contributes to the model significantly and moderates the information from financial and non-financial variables, which can be seen from the smaller Wald statistics of financial and non-financial variables compared to Model 1. Nevertheless, a model based on ledger data, and selected financial and non-financial variables, outperforms Models 1 and 2 that use only external or internal information alone. The results are consistent with hypotheses H1 through H4. Ledger data variables have economically significant prediction power, even over traditionally used financial and background variables; coefficients and Wald statistics both show highest values for variables describing past payment behavior. Moreover, Model 3 that combines external financial and background information to ledger data variables has a higher R square value and better classification accuracy compared to Models 1 and 2. However, the difference between the accuracy of Model 2a and Model 3 might not be significant enough to reject the null hypothesis that the models do not significantly differ from each other and to accept Hypothesis 3; naturally the goodness of fit increases when more variables are introduced to a model.

All variables introduced in the previous models keep their information content fairly intact. The only notable difference is that equity ratio loses some of its significance and its coefficient turns slightly positive. However, equity ratio has small information content also in Model 1 that is based on financial and non-financial variables alone. One explanation might be that equity ratio does not best describe leverage in this industry or that it does not directly correlate with payment behavior; firms with refined ratings tend to save less cash and have significantly more long term debt (Almeida, Campello & Weisbach, 2004; Tang, 2006). As ratings are based on payment defaults among other financial and non-financial aspects, a firm with an improved rating based on other variables than equity ratio, might have high amount of long-term debt compared to other firms and consequently a low equity ratio. Additionally, Laitinen and Laitinen (2009) argue that equity ratio reported in financial statements is upwards biased for firms in financial distress. Thus the use of equity ratio is controversial; it is widely used yet it is subject to manipulation and can be easily misconstrued.

Wilson et al. (2000) use payment information from an index called D&B Payment Score and show that accounting information predicts payment behavior much poorer than it does for corporate default. This is a natural consequence of the difference in publication between accounting and payment information; at best financial statements are reported quarterly whereas client's cash flow transactions update to the ledger on a daily basis. My results support the findings of Wilson et al. (2000); financial and background variables alone have poorer prediction power on payment failure compared to payment history variables.

Clearly, however, the use of financial statements and other background information improves a model's accuracy in payment behavior prediction. According to Carey and Hrycay (2001), rating agencies assign their ratings based on stress tests and a borrower's projected condition in the downside scenario (a 'through-the-cycle method') while banks and other companies grant credit according to clients' current condition (point-in-time method).[31] Similar difference is present in my results; Asiakastieto Ltd's rating scores "analyze a firm's financial and background information, as well as estimate its probability of facing financial difficulties or bankruptcy within the next 3 years" (Asiakastieto Ltd), while financial ratios offer a point-in-time analysis of certain key figures.

A model where Asiakastieto Ltd's rating scores are added to the Model 2a using primarily only ledger variables is shown in Model 4. The –2 Log likelihood and the pseudo R-squares show better values for the model based on combined information compared to Model 2a using ledger variables. Also the Nagelkerke R-Square is somewhat higher at 0.512 (0.505) for Model 4 (Model 2a). Model 4 also classifies slightly better: 83.2% (83.5%) of non-failed and 76.7% (75.0%) of failed firms are correctly classified.

Asiakastieto Ltd's letter ratings assigned at the end of 2010 are significantly related to the likelihood of payment failure during June 2011 – May 2012. The results implicate that a firm with strong financial and background variables, followed by an assignment of a higher Rating Alfa letter score, is less likely to fail in its payments. A high Rating Alfa score thus signals punctual payment behavior and work as a certification of quality, whether the score measures financial health or payment morale (see, also, Hsueh & Kidwell, 1988; Millon and Thakor, 1985, on the certification role of rating services). It would indeed seem that payment failure is a sign of impending failure as shown by Wilson et al. (2000). However this result does not indicate that some firms would not pay poorly for reasons other than financial difficulties; as in this thesis, larger firms seem to be associated with poor payment habits more often than smaller firms, hinting of a possible misuse of economies of scale – or efficiency of working capital management – depending on the point of view.

[31] Treacy and Carey (1998) argue that credit agencies' method is too expensive for banks, which implies a continuing need for the use of point-in-time method.

On the other hand, Model 3 using selected financial and non-financial variables outperforms Model 4 using ready rating scores. It might be that some variables contributing to the current ratings reflect the risk of the firms used in this study, while some variables do not. If Asiakastieto Ltd wishes to expand its services towards more customer-oriented unique rating services, its rating scoring model could be modified according to the customer company in question, and more importantly, according to the definition of failure and its severity depending on each company's needs and characteristics.

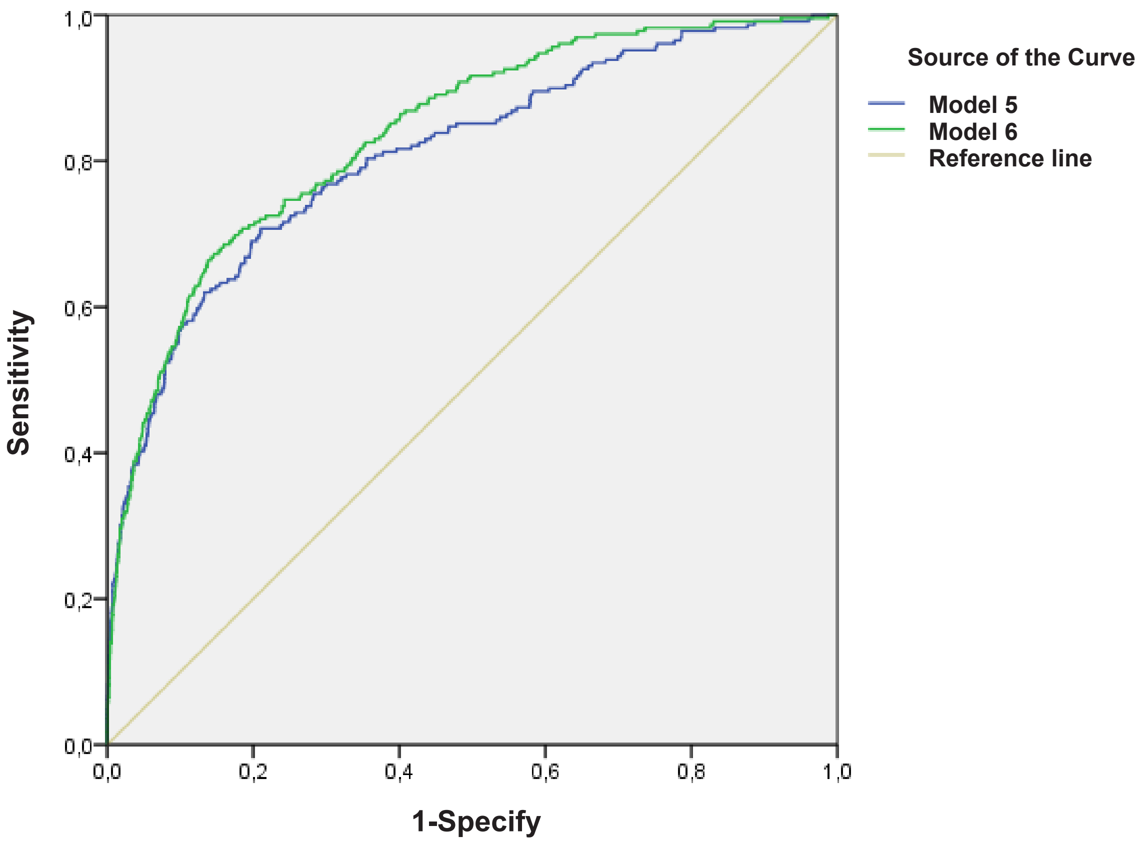
4.2 Models Using the Whole Sample

The weighted whole sample of 7741 failed and 7741 non-failed firms is used to account also for firms for which ledger data are available but financial statements are not. This whole sample better represents the clientele of Company X and thus the final comparisons of models are presented using this sample.

Model 5 Panel 1 shows the model summary tests of the model using primarily only ledger information, and Model 6 Panel 1 presents the model summary tests using the sample data with rating score variables in addition to ledger variables. The models are compared in terms of classification accuracy, Nagelkerke R-Squares, the –2 Log Likelihood test, the pseudo R-squares, Type I and Type II errors and the ROC curve as well as the two-sample Kolmogorov-Smirnov test. As expected, the model with additional external information, in the form of rating scores, better predicts a firm's probability to fail in its payments and become an unprofitable client. Model 6 using both ledger data and ready rating scores has Nagelkerke R-Square of 0.425, exceeding that of Model 5 using only ledger data variables (0.382). Also the –2 Log Likelihood is lower and the pseudo R-squares higher for the model combining ledger data to existing credit scores, supporting the use of combined information. In addition, the model using combined data (ledger data) correctly classifies 81.1% (81.3%) of the non-failed and 70.7% (65.9%) of the failed firms. Even though the ledger data variables still have very high Wald statistics, the rating scores clearly add information to the model, consistently with Hypothesis 3.

Figure 2 shows the ROC curves of Model 5 (represented by the blue line) and Model 6 (represented by the green line). By convention, models predicting credit default are evaluated by using power curves, which make the predictive power of a model quantifiable (see, among others, Birdsall, 1973; Hanley and McNeil, 1982; Hanley, 1989; Pepe, 2002; Sobehart, Keenan & Stein, 2000; Swets, 1988, 1996). According to Stein (2005), "A receiver operator characteristic (ROC) curve plots the Type II error against one minus the Type I error" and describes the percentage of non-failing firms that must be unintentionally denied credit (Type II error) to avoid offering credit to a specific percentage of failing firms (1-Type I error) when a certain failure model is used. ROC analysis produces a cost-benefit analysis of some sort, since extending credit to a failing firm is usually associated with higher costs compared to not extending credit, or granting credit with overly strict terms, to a non-failing firm. As the true costs of a payment failure are not known in this study, ROC analysis cannot be used to determine the optimal cut-off that minimizes costs for Company X. However, ROC curves can be used to analyze which model, Model 5 or Model 6, offers highest prediction power. Figure 2 shows that Model 6 that combines internal ledger and

Figure 2: ROC Curve



external rating score information, represented by the green line, has better accuracy in payment failure prediction, as hypothesized in H3.

Moreover, I use the Two-Sample Kolmogorov-Smirnov test (KS-test) to estimate the two models' goodness of fit; this test has the advantage that it does not make any assumptions about the distribution of data. Model 6 classifies firms somewhat better also according to this test: Kolmogorov-Smirnov Z value is somewhat higher 7.854 for Model 6 compared to Model 5 (7.418), both statistics being significant at the 1% level. Type I error of incorrectly granting credit to a failing firm is 34.1% for Model 5 and 29.3% for Model 6 whilst Type II error of incorrectly denying a non-failing firm credit is 18.7% for Model 5 and 18.9% for Model 6. Overall, Model 6 outperforms Model 5 once again, implying that Company X would gain from the use of its ledger data as the extension of Rating Alfa scores based on external information.

The whole sample models perform slightly poorer compared to the models using the same variables but with the reduced sample. This may be a result from the lack of financial data available for some 1600 firms, that is, small firms. In addition to more difficult rating process, it might be that smaller firms are less prone to a systematic payment behavior and this is why Models 5 and 6 are slightly poorer at classifying these firms as either failed or non-failed. Large firms have more established cash in- and outflows and probably more routines in the way they pay their bills. Smaller firms may have such cyclical or unstable cash flows that payment behavior may vary depending on business cycle.

4.3 Robustness Check – Testing of a More Severe Default

As the main limitation of this study is the unique company-related definition of failure, I expand the research by testing ledger variables' prediction power on a more severe payment default, defined by Basel II regulations and widely used by credit agencies and prior literature (see, among others, Jappelli & Pagano, 2000; Kocenda & Vojtek, 2009; Minussi, Soopramanien

& Worthington, 2007). According to Basel II regulations, default is defined by a delay equal or longer than 90 days on any obligation (Basel Committee on Banking Supervision, 2006). In Model 7 the dependent variable 'DEFAULT' takes the value of one (1) if at least one bill has been paid at least 90 days after the due date during June 2011 – May 2012, and zero (0) otherwise.

If the definition of default according to Basel Committee describes financial distress more precisely than Company X's definition of client profitability measured by payment failure, then results shown in Model 7 reinforces that ledger variables accurately predict both financial distress and poor paying habits. Ledger variables describing payment history, late8-29 and late30+, are significant at the 1% level. Similarly to Models 1-6, firm age is negatively related to default likelihood and firm size increases the probability of default, both variables being significant at the 1% level. Business relationship's age with Company X is inversely related to the probability of default, although the coefficient loses some of its significance. The results confirm the robustness of ledger variables in corporate failure prediction; ledger data are not only useful in payment behavior prediction but they can be also used successfully to predict actual default.

5 Summary and Conclusion

Prior empirical studies in the credit risk prediction field differ from each other fundamentally in terms of failure definitions.[32] Definitions of failure have varied from severe consequences such as liquidation, bankruptcy and reorganization to inability to pay debts and overdrawn bank accounts, followed by even milder versions of failure such as bond defaults and non-payment of creditors (see Karels and Prakash, 1987). Officially registered payment defaults have been used by Laitinen and Laitinen (2009). According to the writers, 10% of payment defaults in Finland are bankruptcies, 2% reorganizations and more than 40% payment private-juridical

[32] See Section 2.2 for further discussion on previous literature on the subject.

draft protests, rest being value-added tax installments and other defaults officially registered by authorities. These, however, only account for *registered* defaults. No study so far has used a definition of the dependent variable, payment failure, similar to this study; at least three payments made at least 30 days after the due date, followed by the client relationship turning unprofitable due to collection and monitoring costs linked to systematic late payments. This definition allows Company X to separate those clients that are profitable in order to, for example, target sales and marketing. It also enables the early recognizing of clients that are more likely to end up in a cycle of paying significantly late, much before more severe and significantly more costly and resources-wasting consequences such as a bankruptcy trial.

In addition, unlike officially registered payment defaults, client firms' systematic payment delays will probably never be publicized, instead, this information accumulates as companies' internal and private relationship knowledge of their client firms. This study analyzes whether companies' internal and private knowledge could be used to better predict payment failure. The results offer a new insight for all companies offering trade credit; ledger transaction data are an undervalued source of important information that is extremely helpful in credit risk management as it is real-time and available for all existing clients. In fact, as client firms' payment behavior may vary significantly from company to company depending on the purchase value and use, internal and private ledger data offer the most accurate and up-to-date information about a client firm's impending failure. For example, Company X finds its clients to be more punctual in their payments towards the company compared to some other companies; Company X's products are required at the beginning of a construction project and thus payment defaults on Company X's bills would likely end the project completely. Consequently, a client firm prefers to delay its payments to "less important" creditors, and continue with its project. If this is the case overall, the most important knowledge comes indeed from inside the company and its ledger. No external information is able to capture the payment behavior of client firms unless payment delays reflect publicly available information such as financial statements. It is left for future research to study how well the definition of payment failure used in this paper suits other industries and companies, or whether some unique modification is needed to make it more accurate.

Theoretical implications

The purpose of this study was to study the use of corporate ledger information in payment behavior prediction and to analyze the possible explanations behind payment failure. Two reasons analyzed were: (1) weak financial situation that makes firms unable to pay their bills on time due to lack of sufficient cash flow, unprofitability and high leverage, and (2) payment pattern that signals for example the misuse of purchase power and thus business relationship in order to delay payments for convenience reasons, or treating trade credit as extended credit.

The results show that weak financials are significantly related to payment failure. The results are supported both by financial variables and by Asiakastieto Ltd's credit rating scores; the lower rated, riskier client firms are associated with payment failure more often compared to their higher rated peers. The results imply that a weakening financial situation is indeed one reason behind poor payment behavior. However, the most dominating factors in payment failure prediction seem to be ledger data variables describing payment history. The results clearly show that ledger variables are the most accurate and offer the most prediction power in failure prediction – the results are moreover supported by the successful use of ledger variables in default prediction, also presented in this thesis.

It is likely that for some of the firms, payment habits are motivated by discrete relationship management with Company X. This result is supported by the evidence that a more established relationship with Company X decreases the likelihood of payment failure. Moreover, Company X has probably accumulated superior knowledge of these firms and is able to manage ties with them better. Another result supporting the two-fold explanation of poor payment behavior is the effect of size: larger firms tend to fail more often. This result could be explained by larger firms' working capital management, or by the misuse of economies of scale, status and relationship with Company X. The question remains whether efficient management is defined by short term maximization of profits and minimization of costs, or whether relationship management in fact turns more profitable in the long run.

Managerial implications

The results show that a company benefits most from a model that combines its own ledger data to external financial and background information. Asiakastieto Ltd's current rating scores that use external ledger information from other companies are significantly related to payment failure, which implies that the sharing of private information might be very useful for companies' credit decision-making not only in the case of new customers but also in modifying the credit terms of existing clients. Naturally more research is needed in the areas of using ledger data in corporate failure prediction, especially across different industries, and the benefits of sharing credit information.

Asiakastieto Ltd and the entire credit rating industry could utilize the results found in this study in the development of credit rating services. Jappelli and Pagano (1999) argue that the presence of formal information exchanges influences macroeconomic performance. Kallberg and Udell (2003) find similar results in their study of information exchanges offered to creditors conducting borrower due diligence. The writers suggest that exchange-generated information is valuable in measuring borrower quality; it goes beyond publicly available information such as financial statements, and it might solve problems arising from credibility problems, data coverage problems and data bias problems.

By combining companies' ledger information to its own information, a credit rating agency could offer real-time data on each client's payment behavior. Consequently, companies could use up-to-date and possibly customized information as a basis for their credit decisions. Accumulated register would be useful especially in industries where companies are not direct competitors of each other but do share the same client base. Naturally a private information exchange pool requires a register base large enough to gain from the cumulative effect of sharing clients. Kallberg and Udell (2003) study the value of business-to-business voluntary information exchange in the US focusing closely on the role and mechanism of the Dun & Bradstreet Corporation (D&B), the world's largest private information exchange. The writers posit that credibility is an important issue for an information exchange and that reputation building is crucial. Thus, an existing credit rating agency with a steady large company pool could have the most potential to start looking at this new approach of credit rating and information sharing.

As noted earlier, clients' payment behavior is not identical to all companies. On the other hand, a company that has a well paying client could yet be warned about the alarming signs of the client's payment difficulties towards a third party – a sign of possible impending failure. Accordingly, information sharing could be useful for all the companies sharing their ledger information via an intermediary. This kind of a wild future idea could significantly reduce the problem of asymmetric information in both intermediaries' and banks' credit rating services, and facilitate companies' credit decisions.

Naturally companies have superior information about their own clients over for example competitors and rating agencies. However, majority of companies do not have adequate resources and knowledge to create their own rating system but it is easier and less costly to use the rating services by an external credit agency. The conclusion of this study is that variables computed using ledger data can be successfully used to predict future payment behavior, and they offer information over and above financial and non-financial background variables. Perhaps it will be useful for a credit rating agency to unite real-time ledger data received from a customer company to its other external data and hence create unique rating services that are more accurate as they are forward-looking, update on a daily basis, and most importantly, the rating services are modified for each customer company by using that company's ledger information and definition of failure. As shown in this study, the dependent variable can be chosen according to the needs of each company;

the profitability of a client firm–creditor firm relationship differs by industry and product. On the other hand, the costs of applying these methods should be measured to ensure that the benefits of a more accurate rating compensate the costs of acquiring it.

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Table I: Industrial classification of firms (7741 firms of original data)

	Frequencies			*Percentages within entire data*			*Percentages within industry category*		
	Failed firms	*Non-failed firms*	*Total*	*% Failed*	*% Non-failed*	*Total*	*% Failed*	*% Non-failed*	*Total*
Construction	137	3564	3701	1.77%	46.04%	47.81%	3.70%	96.30%	100.00%
Manufacturing	23	1117	1140	0.30%	14.43%	14.73%	2.02%	97.98%	100.00%
Wholesale and retail trade; repair of motor vehicles and motorcycles	18	604	622	0.23%	7.80%	8.04%	2.89%	97.11%	100.00%
Administrative and support service activities	13	434	447	0.17%	5.61%	5.77%	2.91%	97.09%	100.00%
Professional, scientific and technical activities	14	355	369	0.18%	4.59%	4.77%	3.79%	96.21%	100.00%
Real estate activities	4	316	320	0.05%	4.08%	4.13%	1.25%	98.75%	100.00%
Industry category missing	5	306	311	0.06%	3.95%	4.02%	1.61%	98.39%	100.00%
Transportation and storage	4	235	239	0.05%	3.04%	3.09%	1.67%	98.33%	100.00%
Arts, entertainment and recreation	1	158	159	0.01%	2.04%	2.05%	0.63%	99.37%	100.00%
Accommodation and food service activities	2	89	91	0.03%	1.15%	1.18%	2.20%	97.80%	100.00%
Water supply; sewerage, waste management and remediation activities	1	71	72	0.01%	0.92%	0.93%	1.39%	98.61%	100.00%
Electricity, gas, steam and air conditioning supply	3	63	66	0.04%	0.81%	0.85%	4.55%	95.45%	100.00%
Other service activities	1	53	54	0.01%	0.68%	0.70%	1.85%	98.15%	100.00%
Information and communication	0	40	40	0.00%	0.52%	0.52%	0.00%	100.00%	100.00%
Financial and insurance activities	1	34	35	0.01%	0.44%	0.45%	2.86%	97.14%	100.00%
Human health and social work activities	1	33	34	0.01%	0.43%	0.44%	2.94%	97.06%	100.00%
Education	0	30	30	0.00%	0.39%	0.39%	0.00%	100.00%	100.00%
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	1	6	7	0.01%	0.08%	0.09%	14.29%	85.71%	100.00%
Public administration and defence; compulsory social security	0	4	4	0.00%	0.05%	0.05%	0.00%	100.00%	100.00%
Total	229	7512	7741	2.96%	97.04%	100.00%			

Table II: Descriptions of variables and their expected signs

Variable name	*Description*	*Expected sign on likelihood of payment failure*
Financial variables (measured at the end of 2010)		
Current_ratio2010	(Financial assets + Current assets) / Short-term debt	–
Equity_ratio2010	100 * (Equity - Provisions) / (Total assets - Advances received)	–
Operating_profit_dummy	Dummy variable takes the value of one (1) if a firm has generated negavite operating profit, and zero (0) otherwise	+
Background variables (measured at the end of 2010)		
ln(size)	Natural logarithm of Total assets	+/–
ln(age)	Natural logarithm of a firm's age in years since registration	–
Industry_risk	Industry propensity to default, (%) measured by Asiakastieto Ltd	+
Past_default_dummy	Dummy variable takes the value of one (1) if any of the following is different from zero: number of past registered payment defaults, number of past registered bankruptcy applications, number of past restructuring applications and number of past reminders of last resort before collection, and zero (0) otherwise	+
TOL	Industrial classification of firms: TOL1=manufacturing, TOL2=transportation and storage, TOL3=professional, scientific and technical activities, TOL4=administrative and support service activities, TOL5=wholesale and retail trade; repair of motor vehicles and motorcycles, and TOL6=construction. TOL1-TOL6 variables measure the higher likelihood of payment failure by firms operating in these business fields, compared to firms operating in other industry categories in the sample.	+
Ledger data variables (measured using ledger data from January 2010 to May 2011)		
late8-29	Natural logarithm of number of payments made 8-29 days after the due date / Natural logarithm of Total assets	+
late30+	Natural logarithm of number of payments made at least 30 days after the due date / Natural logarithm of Total assets	+
RelativeLate	Number of payments made at least eight days after the due date / Total number of purchases made by the same firm	+
RelativeLate30+	Number of payments made at least 30 days after the due date / Number of payments made at least eight days after the due date, by the same firm	+
ln(RelationshipAge)	Natural logarithm of a client relationship's age in years since first purchase from Company X	–
Rating score variables (measured at the end of 2010)		
RatingAlfa	Rating scores: AAA through B are letter rating scores assigned by Asiakastieto Ltd that "analyze a firm's financial and background information, as well as estimate its probability of facing financial difficulties or bankruptcy within the next three years". Letter ratings AAA-B measure the lower likelihood of payment failure by firms that have been assigned these rating scores, compared to the firms with the lowest rating C.	–
Dependent variables (measured using ledger data from June 2011 to May 2012		
Payment failure event	Dependent variable takes the value of one (1) if a firm pays three or more of its bills at least 30 days after the due date during June 2011 - May 2012, and zero (0) otherwise	n.a.
Default event according to Basel II	Dependent variable takes the value of one (1) if a firm pays at least one of its bills at least 90 days after the due date during June 2011 - May 2012, and zero (0) otherwise	n.a

Table III: T-test of Comparison of Means

Test statistics using the reduced original sample of 180 failed and 5946 non-failed firms. * And ** And * next to the p-values denote significance at the 1%, 5% and 10% levels, respectively.**

Variable	***Failed firms***			***Non-failed firms***			***Comparison of means***	
	Mean	*Median*	*Standard deviation*	*Mean*	*Median*	*Standard deviation*	*T test statistics*	*p-value*
Relationship Age (in years)	6.12	6.17	2.67	6.33	6.58	2.76	1.02	0.31
Age (in years)	15.96	13.00	15.25	18.59	17.00	14.48	2.40	0.02**
Current ratio 2010	1.40	1.10	1.33	2.68	1.40	15.05	5.88	0.00***
Equity ratio (%) 2010	18.59	25.95	51.05	35.74	40.10	79.32	2.88	0.00***
Total balance sheet (mEur)	68.27	1.10	391.34	18.33	0.71	296.39	-1.70	0.09*
Industry risk (propensity to default)	8.85	9.10	3.45	7.85	7.70	3.51	-3.74	0.00***
Past default dummy	0.04	0.00	0.19	0.01	0.00	0.10	-1.94	0.05**
Operating profit dummy	0.32	0.00	0.47	0.25	0.00	0.43	-1.89	0.06*
RelativeLate	0.32	0.27	0.31	0.14	0.00	0.24	-7.95	0.00***
RelativeLate30+	0.20	0.13	0.26	0.07	0.00	0.22	-6.60	0.00***
late8-29	0.15	0.15	0.10	0.04	0.00	0.06	-14.68	0.00***
late30+	0.07	0.05	0.08	0.01	0.00	0.03	-10.32	0.00***

Notes:

Current ratio = (Financial assets + Current assets) / (Short-term debt)
Reference values:
Over 2.0 = good
1.0 - 2.0 = satisfactory
Below 1.0 = weak

Equity ratio, % = 100 ∗ (Equity - Provisions) / (Total assets - Advances received)
Reference values:
Over 40 % = good
20 - 40 % = satisfactory
Below 20 % = weak

Model 1: Logistic regression model based on financial & non-financial variables, reduced sample

The weighted (reduced) sample in the regression consists of Company X's business-to-business client firms, which have made purchases during January 2010 – May 2012 and for which financial statement data is available. The reduced sample consists of some 5946 failed and 5946 non-failed firms. The independent variables are measured by Asiakastieto Ltd at the end of 2010. Financial variables: Current_ratio2010 describes the liquidity of a firm, Equity_ratio2010 describes the relation of equity and total assets, and Operating_profit_dummy takes the value of one if a firm has generated negative operating profit, and zero otherwise. Background non-financial variables: Industry_risk measures the propensity to default (%) in a firm's business field, ln(size) and ln(age) are the natural logarithm of total assets and firm age in years since registration, respectively. TOL figures describe the higher risk of payment failure in following industries compared to other industries; TOL1=manufacturing, TOL2=transportation and storage, TOL3=professional, scientific and technical activities, TOL4=administrative and support service activities, TOL5=wholesale and retail trade; repair of motor vehicles and motorcycles, and TOL6=construction. The dependent variable is measured using Company X's ledger data, and it takes the value of one if a firm has paid at least three of its bills at least 30 days after the due date during June 2011 – May 2012, and zero otherwise. All variables and their formulas are presented in Appendix 1. *** And ** And * next to the p-values denote significance at the 1%, 5% and 10% levels, respectively.

Panel 1: Model summary tests

-2 Log likelihood	*Cox & Snell R Square*	*Nagelkerke R Square*
14071.240	0.184	0.245

Panel 2: Parameters of the binary logistic regression model

Variables	*B*	*S.E.*	*Wald*	*df*	*p-value*	*Exp(B)*
Current_ratio2010	-0.171	0.016	111.206	1	0.000***	0.843
Equity_ratio2010	-0.004	0.001	60.063	1	0.000***	0.996
Industry_risk	0.077	0.008	91.723	1	0.000***	1.080
ln(size)	0.371	0.012	983.879	1	0.000***	1.450
ln(age)	-0.431	0.029	224.501	1	0.000***	0.650
Past_default_dummy	0.899	0.156	33.224	1	0.000***	2.458
Operating_profit_dummy	0.249	0.049	25.590	1	0.000***	1.283
TOL (others)			449.155	6	0.000***	
TOL(1)	0.617	0.087	50.339	1	0.000***	1.854
TOL(2)	0.674	0.144	21.971	1	0.000***	1.961
TOL(3)	1.529	0.114	180.775	1	0.000***	4.614
TOL(4)	1.058	0.116	82.839	1	0.000***	2.881
TOL(5)	0.745	0.098	58.121	1	0.000***	2.107
TOL(6)	1.575	0.085	345.827	1	0.000***	4.830
Constant	-5.599	0.207	728.445	1	0.000***	0.004

Panel 3: Classification accuracy of the model[a]

Observed	**Estimation data:**		
		Predicted	
	Non-failed	Failed	*Correct, %*
Non-failed	3992	1954	67.1
Failed	1652	4294	72.2
Overall Percentage			69.7

[a]The cut value is 0.500

Model 2a: Logistic regression model based on ledger variables, reduced sample

The weighted (reduced) sample in the regression consists of Company X's business-to-business client firms, which have made purchases during January 2010 – May 2012 and for which financial statement data is available. The reduced sample consists of some 5946 failed and 5946 non-failed firms. The independent variables describing past payment behavior are measured from Company X's ledger, using transaction data from January 2010 to May 2011. Past payment behavior variables in Model 2a: Variable late8-29 measures the natural logarithm of number of bills paid 8-29 days after the due date, divided by natural logarithm of total assets in 2010. Variable late30+ measures the natural logarithm of number of bills paid at least 30 days after the due date, divided by natural logarithm of total assets in 2010. Past payment behavior variables in Model 2b:Variable RelativeLate measures the number of bills paid at least eight days after the due date, divided by the total number of purchases made by the same firm. Variable RelativeLate30+ measures the number of bills paid at least 30 days after the due date, divided by the total number of bills paid at least eight days after the due date by the same firm. In addition, ln(RelationshipAge) is the natural logarithm of the client relationship age in years. The dependent variable is measured using Company X's ledger data, and it takes the value of one if a firm has paid at least three of its bills at least 30 days after the due date during June 2011 – May 2012, and zero otherwise. All variables and their formulas are presented in Appendix 1. *** And ** And * next to the p-values denote significance at the 1%, 5% and 10% levels, respectively.

Panel 1a: Model summary tests

-2 Log likelihood	*Cox & Snell R Square*	*Nagelkerke R-Square*
10827.934	0.378	0.505

Panel 2a: Parameters of the binary logistic regression model

Variables	*B*	*S.E.*	*Wald*	*df*	*p-value*	*Exp(B)*
ln(RelationshipAge)	-0.328	0.045	52.684	1	0.000***	0.720
late8-29	13.317	0.348	1468.485	1	0.000***	607476.608
late30+	15.287	0.673	516.001	1	0.000***	4357837.442
ln(size)	0.271	0.012	546.618	1	0.000***	1.312
ln(age)	-0.317	0.035	83.035	1	0.000***	0.728
Constant	-4.029	0.163	613.163	1	0.000***	0.018

Panel 3a: Classification accuracy of the model[a]

Observed	**Estimation data:**		
	Predicted		
	Non-failed	Failed	*Correct, %*
Non-failed	4963	980	83.5
Failed	1486	4459	75.0
Overall Percentage			79.3

[a]The cut value is 0.500

Model 2b: Logistic regression model based on ledger variables, reduced sample

Panel 1b: Model summary tests

-2 Log likelihood	*Cox & Snell R Square*	*Nagelkerke R Square*
13862.880	0.198	0.264

Panel 2b: Parameters of the binary logistic regression model

Variables	B	S.E.	Wald	df	*p-value*	Exp(B)
ln(RelationshipAge)	0.061	0.041	2.201	1	0.138	1.063
RelativeLate	2.584	0.085	917.879	1	0.000***	13.250
RelativeLate30+	1.789	0.092	378.583	1	0.000***	5.983
ln(size)	0.264	0.011	628.119	1	0.000***	1.302
ln(age)	-0.442	0.031	208.169	1	0.000***	0.643
Constant	-3.460	0.151	526.422	1	0.000***	0.031

Panel 3b: Classification accuracy of the model[a]

Observed	**Estimation data:**		
	Predicted		
	Non-failed	Failed	*Correct, %*
Non-failed	4434	1512	74.6
Failed	2015	3931	66.1
Overall Percentage			70.3

[a]The cut value is 0.500

Model 3: Logistic regression model based on ledger information and financial & non-financial variables, reduced sample

The weighted (reduced) sample in the regression consists of Company X's business-to-business client firms, which have made purchases during January 2010 – May 2012 and for which financial statement data is available. The reduced sample consists of some 5946 failed and 5946 non-failed firms. The independent variables are measured partly by Asiakastieto Ltd at the end of 2010, and partly constructed using Company X's ledger transaction data from January 2010 to May 2011. Financial variables: Current_ratio2010 describes the liquidity of a firm, Equity_ratio2010 describes the relation of equity and total assets, and Operating_profit_dummy takes the value of one if a firm has generated negative operating profit, and zero otherwise. Background non-financial variables: Industry_risk measures the propensity to default (%) in a firm's business field, ln(size) and ln(age) are the natural logarithm of total assets and firm age in years since registration, respectively. TOL figures describe the higher risk of payment failure in following industries compared to other industries; TOL1=manufacturing, TOL2=transportation and storage, TOL3=professional, scientific and technical activities, TOL4=administrative and support service activities, TOL5=wholesale and retail trade; repair of motor vehicles and motorcycles, and TOL6=construction. Past payment behavior variables: Variable late8-29 measures the natural logarithm of number of bills paid 8-29 days after the due date, divided by natural logarithm of total assets in 2010. Variable late30+ measures the natural logarithm of number of bills paid at least 30 days after the due date, divided by natural logarithm of total assets in 2010. In addition, ln(RelationshipAge) is the natural logarithm of the client relationship age in years. The dependent variable is measured using Company X's ledger data, and it takes the value of one if a firm has paid at least three of its bills at least 30 days after the due date during June 2011 – May 2012, and zero otherwise. All variables and their formulas are presented in Appendix 1. *** And ** And * next to the p-values denote significance at the 1%, 5% and 10% levels, respectively.

Panel 1: Model summary tests

-2 Log likelihood	*Cox & Snell R Square*	*Nagelkerke R Square*
10248.797	0.408	0.544

Panel 2: Parameters of the binary logistic regression model

Variables	*B*	*S.E.*	*Wald*	*df*	*p-value*	*Exp(B)*
ln(RelationshipAge)	-0.511	0.048	111.194	1	0.000***	0.600
late8-29	12.168	0.373	1064.498	1	0.000***	192600.209
late30+	16.651	0.711	547.734	1	0.000***	17039737.308
ln(size)	0.399	0.014	812.438	1	0.000***	1.490
ln(age)	-0.227	0.037	37.872	1	0.000***	0.797
Industry_risk	0.079	0.010	67.350	1	0.000***	1.082
Current_ratio2010	-0.063	0.013	22.103	1	0.000***	0.939
Equity_ratio2010	0.001	0.001	3.517	1	0.061*	1.001
Past_default_dummy	0.412	0.227	3.286	1	0.070*	1.510
Operating_profit_dummy	0.324	0.060	29.698	1	0.000***	1.383
TOL2 (others)			222.131	6	0.000***	
TOL2(1)	0.339	0.104	10.549	1	0.001***	1.404
TOL2(2)	0.290	0.165	3.090	1	0.079*	1.336
TOL2(3)	1.302	0.131	98.724	1	0.000***	3.677
TOL2(4)	1.170	0.135	75.486	1	0.000***	3.222
TOL2(5)	0.800	0.109	53.745	1	0.000***	2.225
TOL2(6)	1.182	0.100	140.884	1	0.000***	3.261
Constant	-7.251	0.250	842.125	1	0.000***	0.001

Panel 3: Classification accuracy of the model[a]

Observed	**Estimation data:**		
	Predicted		
	Non-failed	Failed	*Correct, %*
Non-failed	4969	974	83.6
Failed	1321	4625	77.8
Overall Percentage			80.7

[a]The cut value is 0.500

Model 4: Logistic regression model based on ledger variables and Rating Alfa, reduced sample

The weighted (reduced) sample in the regression consists of Company X's business-to-business client firms, which have made purchases during January 2010 – May 2012 and for which financial statement data is available. The reduced sample consists of some 5946 failed and 5946 non-failed firms. The independent variables describing past payment behavior are measured from Company X's ledger, using transaction data from January 2010 to May 2011. Past payment behavior variables: Variable late8-29 measures the natural logarithm of number of bills paid 8-29 days after the due date, divided by natural logarithm of total assets in 2010. Variable late30+ measures the natural logarithm of number of bills paid at least 30 days after the due date, divided by natural logarithm of total assets in 2010. In addition, ln(RelationshipAge) is the natural logarithm of the client relationship age in years. Letter rating variables refer to rating scores Asiakastieto Ltd's has assigned to each firm in the sample at the end of 2010, and they measure each letter rating's association to payment failure, compared to lowest rating 'C'. The dependent variable is measured using Company X's ledger data, and it takes the value of one if a firm has paid at least three of its bills at least 30 days after the due date during June 2011 – May 2012, and zero otherwise. All variables and their formulas are presented in Appendix 1. *** And ** And * next to the p-values denote significance at the 1%, 5% and 10% levels, respectively.

Panel 1: Model summary tests

-2 Log likelihood	*Cox & Snell R Square*	*Nagelkerke R Square*
10727.298	0.384	0.512

Panel 2: Parameters of the binary logistic regression model

Variables	*B*	*S.E.*	*Wald*	*df*	*p-value*	*Exp(B)*
ln(RelationshipAge)	-0.288	0.046	39.244	1	0.000***	0.750
late8-29	12.733	0.356	1276.289	1	0.000***	338643.472
late30+	15.356	0.695	488.601	1	0.000***	4669163.883
ln(size)	0.313	0.013	582.644	1	0.000***	1.367
ln(age)	-0.242	0.037	43.452	1	0.000***	0.785
Rating score (C)			98.344	6	0.000***	
AAA	-1.026	0.149	47.381	1	0.000***	0.359
AA+	-1.088	0.138	62.301	1	0.000***	0.337
AA	-0.589	0.142	17.192	1	0.000***	0.555
A+	-0.601	0.133	20.483	1	0.000***	0.548
A	-0.502	0.135	13.822	1	0.000***	0.605
B	-0.545	0.166	10.764	1	0.001***	0.580
Constant	-4.107	0.216	362.553	1	0.000***	0.016

Panel 3: Classification accuracy of the model[a]

Observed	**Estimation data:**		
		Predicted	
	Non-failed	Failed	*Correct, %*
Non-failed	4942	1001	83.2
Failed	1387	4559	76.7
Overall Percentage			79.9

[a]The cut value is 0.500

Model 5: Logistic regression model based on ledger variables, whole sample
The weighted (whole) sample in the regression consists of Company X's business-to-business client firms, which have made purchases during January 2010 – May 2012. The whole sample consists of some 7741 failed and 7741 non-failed firms. The independent variables describing past payment behavior are measured from Company X's ledger, using transaction data from January 2010 to May 2011. Past payment behavior variables: Variable late8-29 measures the natural logarithm of number of bills paid 8-29 days after the due date, divided by natural logarithm of total assets in 2010. Variable late30+ measures the natural logarithm of number of bills paid at least 30 days after the due date, divided by natural logarithm of total assets in 2010. In addition, ln(RelationshipAge) is the natural logarithm of the client relationship age in years. The dependent variable is measured using Company X's ledger data, and it takes the value of one if a firm has paid at least three of its bills at least 30 days after the due date during June 2011 – May 2012, and zero otherwise. All variables and their formulas are presented in Appendix 1. *** And ** And * next to the p-values denote significance at the 1%, 5% and 10% levels, respectively.

Panel 1: Model summary tests

-2 Log likelihood	*Cox & Snell R Square*	*Nagelkerke R Square*
16233.074	0.287	0.382

Panel 2: Parameters of the binary logistic regression model

Variables	*B*	*S.E.*	*Wald*	*df*	*p-value*	*Exp(B)*
ln(RelationshipAge)	-0.288	0.035	66.386	1	0.000***	0.750
late8-29	10.359	0.303	1170.939	1	0.000***	31524.496
late30+	13.498	0.634	453.405	1	0.000***	728130.641
ln(size)	0.292	0.011	717.889	1	0.000***	1.339
ln(age)	-0.385	0.027	202.447	1	0.000***	0.680
Constant	-3.700	0.155	572.971	1	0.000***	0.025

Panel 3: Classification accuracy of the model[a]

Observed	**Estimation data:**		
		Predicted	
	Non-failed	Failed	*Correct, %*
Non-failed	6295	1446	81.3
Failed	2637	5104	65.9
Overall Percentage			73.6

[a]The cut value is 0.500

Model 6: Logistic regression model based on ledger variables and Rating Alfa, whole sample

The weighted (whole) sample in the regression consists of Company X's business-to-business client firms, which have made purchases during January 2010 – May 2012 and for which financial statement data is available. The whole sample consists of some 7741 failed and 7741 non-failed firms. The independent variables describing past payment behavior are measured from Company X's ledger, using transaction data from January 2010 to May 2011. Past payment behavior variables: Variable late8-29 measures the natural logarithm of number of bills paid 8-29 days after the due date, divided by natural logarithm of total assets in 2010. Variable late30+ measures the natural logarithm of number of bills paid at least 30 days after the due date, divided by natural logarithm of total assets in 2010. In addition, ln(RelationshipAge) is the natural logarithm of the client relationship age in years. Letter rating variables refer to rating scores Asiakastieto Ltd's has assigned to each firm in the sample at the end of 2010, and they measure each letter rating's association to payment failure, compared to lowest rating 'C'. The dependent variable is measured using Company X's ledger data, and it takes the value of one if a firm has paid at least three of its bills at least 30 days after the due date during June 2011 – May 2012, and zero otherwise. All variables and their formulas are presented in Appendix 1. *** And ** And * next to the p-values denote significance at the 1%, 5% and 10% levels, respectively.

Panel 1: Model summary tests

-2 Log likelihood	*Cox & Snell R Square*	*Nagelkerke R Square*
15527.607	0.318	0.425

Panel 2: Parameters of the binary logistic regression model

Variables	*B*	*S.E.*	*Wald*	*df*	*p-value*	*Exp(B)*
ln(RelationshipAge)	-0.262	0.037	51.051	1	0.000***	0.770
late8-29	10.376	0.310	1118.483	1	0.000***	32065.614
late30+	14.199	0.670	448.861	1	0.000***	1467348.232
ln(size)	0.359	0.012	890.046	1	0.000***	1.432
ln(age)	-0.145	0.030	23.213	1	0.000***	0.865
Rating score (C)			637.305	6	0.000***	
AAA	-2.271	0.114	398.786	1	0.000***	0.103
AA+	-2.249	0.101	497.758	1	0.000***	0.106
AA	-1.790	0.100	319.168	1	0.000***	0.167
A+	-1.672	0.095	308.472	1	0.000***	0.188
A	-1.159	0.095	148.476	1	0.000***	0.314
B	-1.034	0.124	69.715	1	0.000***	0.356
Constant	-3.701	0.196	357.531	1	0.000***	0.025

Panel 3: Classification accuracy of the model[a]

Observed	**Estimation data:**		
	Predicted		
	Non-failed	Failed	*Correct, %*
Non-failed	6275	1466	81.1
Failed	2265	5476	70.7
Overall Percentage			75.9

[a]The cut value is 0.500

Model 7: Logistic regression model based on ledger variables, testing default defined by Basel II, whole sample

The weighted (whole) sample in the regression consists of Company X's business-to-business client firms, which have made purchases during January 2010 – May 2012. The whole sample consists of some 7741 failed and 7741 non-failed firms. The independent variables describing past payment behavior are measured from Company X's ledger, using transaction data from January 2010 to May 2011. Past payment behavior variables: Variable late8-29 measures the natural logarithm of number of bills paid 8-29 days after the due date, divided by natural logarithm of total assets in 2010. Variable late30+ measures the natural logarithm of number of bills paid at least 30 days after the due date, divided by natural logarithm of total assets in 2010. In addition, ln(RelationshipAge) is the natural logarithm of the client relationship age in years. The dependent variable is measured using Company X's ledger data, and it takes the value of one if a firm has paid at least one of its bills at least 90 days after the due date during June 2011 – May 2012, and zero otherwise. All variables and their formulas are presented in Appendix 1. *** And ** And * next to the p-values denote significance at the 1%, 5% and 10% levels, respectively.

Panel 1: Model summary tests

-2 Log likelihood	*Cox & Snell R Square*	*Nagelkerke R Square*
14892.357	0.094	0.125

Panel 2: Parameters of the binary logistic regression model

Variables	*B*	*S.E.*	*Wald*	*df*	*p-value*	*Exp(B)*
ln(RelationshipAge)	-0.071	0.037	3.688	1	0.055*	0.931
late8-29	4.055	0.315	165.491	1	0.000***	57.713
late30+	10.439	0.648	259.310	1	0.000***	34167.688
ln(size)	0.134	0.010	187.031	1	0.000***	1.143
ln(age)	-0.121	0.029	17.607	1	0.000***	0.886
Constant	-1.852	0.136	186.431	1	0.000***	0.157

Panel 3: Classification accuracy of the model[a]

Observed	**Estimation data:**		
	Predicted		
	Non-default	Default	*Correct, %*
Non-default	4245	1536	73.4
Default	2740	3044	52.6
Overall Percentage			63.0

[a]The cut value is 0.500

Model 1: Correlation Matrix

	Constant	*Current_ ratio2010*	*Equity_ ratio2010*	*Industry_risk*	*ln(size)*	*ln(age)*	*Past_default_ dummy*	*Operating_ profit_dummy*	*TOL(1)*	*TOL(2)*	*TOL(3)*	*TOL(4)*	*TOL(5)*	*TOL(6)*
Constant	1.000	-0.112	0.065	-0.448	-0.851	-0.085	-0.029	-0.175	-0.214	-0.192	-0.343	-0.297	-0.191	-0.312
Current_ratio2010	-0.112	1.000	-0.334	-0.015	0.060	-0.078	-0.024	0.036	-0.013	0.036	-0.032	0.041	-0.009	-0.013
Equity_ratio2010	0.065	-0.334	1.000	-0.007	-0.078	-0.127	0.069	0.291	-0.020	0.022	-0.032	-0.042	0.034	-0.038
Industry_risk	-0.448	-0.015	-0.007	1.000	0.250	0.084	0.001	0.055	-0.085	-0.079	0.039	-0.132	-0.126	-0.420
ln(size)	-0.851	0.060	-0.078	0.250	1.000	-0.295	0.024	0.125	0.026	0.095	0.171	0.167	0.048	0.211
ln(age)	-0.085	-0.078	-0.127	0.084	-0.295	1.000	-0.010	-0.064	-0.081	-0.086	0.005	-0.034	-0.124	-0.108
Past_default_dummy	-0.029	-0.024	0.069	0.001	0.024	-0.010	1.000	0.013	0.007	0.011	-0.001	0.013	0.013	-0.024
Operating_profit_ dummy	-0.175	0.036	0.291	0.055	0.125	-0.064	0.013	1.000	-0.054	0.001	0.012	0.045	-0.013	-0.042
TOL(1)	-0.214	-0.013	-0.020	-0.085	0.026	-0.081	0.007	-0.054	1.000	0.363	0.443	0.447	0.534	0.645
TOL(2)	-0.192	0.036	0.022	-0.079	0.095	-0.086	0.011	0.001	0.363	1.000	0.279	0.293	0.335	0.428
TOL(3)	-0.343	-0.032	-0.032	0.039	0.171	0.005	-0.001	0.012	0.443	0.279	1.000	0.361	0.396	0.495
TOL(4)	-0.297	0.041	-0.042	-0.132	0.167	-0.034	0.013	0.045	0.447	0.293	0.361	1.000	0.411	0.564
TOL(5)	-0.191	-0.009	0.034	-0.126	0.048	-0.124	0.013	-0.013	0.534	0.335	0.396	0.411	1.000	0.604
TOL(6)	-0.312	-0.013	-0.038	-0.420	0.211	-0.108	-0.024	-0.042	0.645	0.428	0.495	0.564	0.604	1.000

Model 2a: Correlation Matrix

	Constant	*ln(Relation- shipAge)*	*late8-29*	*late30+*	*ln(size)*	*ln(age)*
Constant	1.000	-.126	-.328	-.008	-.826	-.058
ln(RelationshipAge)	-.126	1.000	-.099	-.042	-.098	-.395
late8-29	-.328	-.099	1.000	-.223	.215	.026
late30+	-.008	-.042	-.223	1.000	-.023	.008
ln(size)	-.826	-.098	.215	-.023	1.000	-.312
ln(age)	-.058	-.395	.026	.008	-.312	1.000

Model 2b: Correlation Matrix

	Constant	*ln(Relation- shipAge)*	*Relative- Late*	*Relative- Late30+*	*ln(size)*	*ln(age)*
Constant	1.000	-0.187	-0.367	-0.004	-0.830	-0.075
ln(RelationshipAge)	-0.187	1.000	0.048	-0.059	-0.072	-0.403
RelativeLate	-0.367	0.048	1.000	-0.113	0.227	0.036
RelativeLate30+	-0.004	-0.059	-0.113	1.000	-0.037	0.021
ln(size)	-0.830	-0.072	0.227	-0.037	1.000	-0.269
ln(age)	-0.075	-0.403	0.036	0.021	-0.269	1.000

Model 3: Correlation Matrix

	Constant	*ln(Relation-shipAge)*	*late8-29*	*late30+*	*ln(size)*	*ln(age)*	*Industry_risk*	*Current_ratio2010*	*Equity_ratio2010*	*Past_default_dummy*	*Operating_profit_dummy*	*TOL(1)*	*TOL(2)*	*TOL(3)*	*TOL(4)*	*TOL(5)*	*TOL(6)*
Constant	1.000	0.031	-0.171	-0.127	-0.839	-0.100	-0.463	-0.154	0.041	-0.024	-0.217	-0.198	-0.153	-0.345	-0.298	-0.180	-0.270
ln(RelationshipAge)	0.031	1.000	-0.101	-0.059	-0.176	-0.369	-0.055	-0.010	-0.075	-0.021	-0.032	-0.085	0.051	-0.022	-0.034	-0.014	-0.128
late8-29	-0.171	-0.101	1.000	-0.261	0.146	-0.028	-0.015	0.074	0.215	0.038	-0.041	-0.068	-0.080	-0.026	-0.055	0.019	-0.060
late30+	-0.127	-0.059	-0.261	1.000	0.067	0.030	0.051	-0.055	-0.024	-0.046	0.104	0.085	0.048	0.062	0.151	0.065	0.114
ln(size)	-0.839	-0.176	0.146	0.067	1.000	-0.200	0.263	0.124	-0.063	0.039	0.162	0.051	0.050	0.178	0.171	0.027	0.203
ln(age)	-0.100	-0.369	-0.028	0.030	-0.200	1.000	0.128	-0.082	-0.120	-0.018	-0.020	-0.069	-0.083	0.017	-0.006	-0.108	-0.057
Industry_risk	-0.463	-0.055	-0.015	0.051	0.263	0.128	1.000	-0.054	-0.004	-0.023	0.074	-0.069	-0.087	0.056	-0.131	-0.124	-0.415
Current_ratio2010	-0.154	-0.010	0.074	-0.055	0.124	-0.082	-0.054	1.000	-0.288	-0.001	-0.029	0.077	0.073	0.031	0.101	0.080	0.113
Equity_ratio2010	0.041	-0.075	0.215	-0.024	-0.063	-0.120	-0.004	-0.288	1.000	0.019	0.253	-0.059	0.016	-0.048	-0.062	0.027	-0.097
Past_default_dummy	-0.024	-0.021	0.038	-0.046	0.039	-0.018	-0.023	-0.001	0.019	1.000	0.005	0.006	0.004	-0.010	0.013	0.009	-0.004
Operating_profit_dummy	-0.217	-0.032	-0.041	0.104	0.162	-0.020	0.074	-0.029	0.253	0.005	1.000	-0.046	0.001	0.055	0.077	0.025	-0.030
TOL(1)	-0.198	-0.085	-0.068	0.085	0.051	-0.069	-0.069	0.077	-0.059	0.006	-0.046	1.000	0.348	0.419	0.436	0.520	0.619
TOL(2)	-0.153	0.051	-0.080	0.048	0.050	-0.083	-0.087	0.073	0.016	0.004	0.001	0.348	1.000	0.271	0.293	0.337	0.411
TOL(3)	-0.345	-0.022	-0.026	0.062	0.178	0.017	0.056	0.031	-0.048	-0.010	0.055	0.419	0.271	1.000	0.362	0.393	0.473
TOL(4)	-0.298	-0.034	-0.055	0.151	0.171	-0.006	-0.131	0.101	-0.062	0.013	0.077	0.436	0.293	0.362	1.000	0.419	0.568
TOL(5)	-0.180	-0.014	0.019	0.065	0.027	-0.108	-0.124	0.080	0.027	0.009	0.025	0.520	0.337	0.393	0.419	1.000	0.592
TOL(6)	-0.270	-0.128	-0.060	0.114	0.203	-0.057	-0.415	0.113	-0.097	-0.004	-0.030	0.619	0.411	0.473	0.568	0.592	1.000

Model 4: Correlation Matrix

	Constant	*ln(Relation-shipAge)*	*late8-29*	*late30+*	*ln(size)*	*ln(age)*	*AAA*	*AA+*	*AA*	*A+*	*A*	*B*
Constant	1.000	-0.151	-0.189	-0.104	-0.695	-0.153	-0.231	-0.306	-0.362	-0.480	-0.549	-0.391
ln(RelationshipAge)	-0.151	1.000	-0.115	-0.039	-0.048	-0.337	-0.010	-0.037	-0.010	0.007	0.047	0.048
late8-29	-0.189	-0.115	1.000	-0.234	0.110	-0.040	0.134	0.090	0.109	0.061	0.000	0.006
late30+	-0.104	-0.039	-0.234	1.000	0.026	0.042	-0.020	0.062	0.075	0.108	0.108	-0.006
ln(size)	-0.695	-0.048	0.110	0.026	1.000	-0.159	-0.255	-0.221	-0.165	-0.065	-0.018	-0.060
ln(age)	-0.153	-0.337	-0.040	0.042	-0.159	1.000	-0.142	-0.091	-0.056	-0.036	0.069	0.020
AAA	-0.231	-0.010	0.134	-0.020	-0.255	-0.142	1.000	0.824	0.779	0.785	0.722	0.607
AA+	-0.306	-0.037	0.090	0.062	-0.221	-0.091	0.824	1.000	0.828	0.846	0.791	0.653
AA	-0.362	-0.010	0.109	0.075	-0.165	-0.056	0.779	0.828	1.000	0.819	0.775	0.633
A+	-0.480	0.007	0.061	0.108	-0.065	-0.036	0.785	0.846	0.819	1.000	0.834	0.673
A	-0.549	0.047	0.000	0.108	-0.018	0.069	0.722	0.791	0.775	0.834	1.000	0.663
B	-0.391	0.048	0.006	-0.006	-0.060	0.020	0.607	0.653	0.633	0.673	0.663	1.000

Model 5: Correlation Matrix

	Constant	*ln(Relation-shipAge)*	*late8-29*	*late30+*	*ln(size)*	*ln(age)*
Constant	1.000	-0.100	-0.283	0.016	-0.913	-0.007
ln(RelationshipAge)	-0.100	1.000	-0.101	-0.031	-0.046	-0.482
late8-29	-0.283	-0.101	1.000	-0.363	0.266	-0.066
late30+	0.016	-0.031	-0.363	1.000	-0.019	-0.014
ln(size)	-0.913	-0.046	0.266	-0.019	1.000	-0.236
ln(age)	-0.007	-0.482	-0.066	-0.014	-0.236	1.000

Model 6: Correlation Matrix

	Constant	*ln(Relation-shipAge)*	*late8-29*	*late30+*	*ln(size)*	*ln(age)*	*AAA*	*AA+*	*AA*	*A+*	*A*	*B*
Constant	1.000	-0.101	-0.201	-0.060	-0.837	-0.152	-0.082	-0.172	-0.266	-0.381	-0.450	-0.310
ln(RelationshipAge)	-0.101	1.000	-0.098	-0.040	-0.042	-0.429	0.041	-0.004	0.001	0.033	0.035	0.057
late8-29	-0.201	-0.098	1.000	-0.346	0.241	-0.057	-0.022	-0.087	-0.019	-0.067	-0.059	-0.045
late30+	-0.060	-0.040	-0.346	1.000	0.042	0.049	-0.122	-0.034	0.005	0.026	0.043	-0.037
ln(size)	-0.837	-0.042	0.241	0.042	1.000	-0.067	-0.209	-0.162	-0.083	0.010	0.031	-0.002
ln(age)	-0.152	-0.429	-0.057	0.049	-0.067	1.000	-0.219	-0.156	-0.106	-0.080	0.067	-0.008
AAA	-0.082	0.041	-0.022	-0.122	-0.209	-0.219	1.000	0.722	0.687	0.690	0.644	0.522
AA+	-0.172	-0.004	-0.087	-0.034	-0.162	-0.156	0.722	1.000	0.761	0.778	0.741	0.587
AA	-0.266	0.001	-0.019	0.005	-0.083	-0.106	0.687	0.761	1.000	0.774	0.752	0.586
A+	-0.381	0.033	-0.067	0.026	0.010	-0.080	0.690	0.778	0.774	1.000	0.806	0.623
A	-0.450	0.035	-0.059	0.043	0.031	0.067	0.644	0.741	0.752	0.806	1.000	0.625
B	-0.310	0.057	-0.045	-0.037	-0.002	-0.008	0.522	0.587	0.586	0.623	0.625	1.000

Model 7: Correlation Matrix

	Constant	*ln(Relation-shipAge)*	*late8-29*	*late30+*	*ln(size)*	*ln(age)*
Constant	1.000	-0.141	-0.192	0.005	-0.811	-0.134
ln(RelationshipAge)	-0.141	1.000	-0.075	-0.002	-0.109	-0.372
late8-29	-0.192	-0.075	1.000	-0.384	0.079	0.092
late30+	0.005	-0.002	-0.384	1.000	-0.049	0.034
ln(size)	-0.811	-0.109	0.079	-0.049	1.000	-0.266
ln(age)	-0.134	-0.372	0.092	0.034	-0.266	1.000