# Revisiting credit risk assessment of SMEs

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# Contents

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## Research objectives

The main aim of the research is to identify reasons pertaining to the issue of financing gap and key aspects of credit risk assessment practices with regard to Small and Medium Enterprises (SMEs). This study tries to bring together, discuss and analyze findings and conclusions of past research in the field with an attempt to establish framework for an optimal credit risk assessment model for SMEs.

# Methodology

This study draws from the similar research papers which have focused on the assessment of credit risk for SMEs. Research method is based on literature review in the field, summary of findings related to the five distinguished aspects of risk assessment practice: choice of models, rating philosophy and time horizon, default definition, determinants of default and dataset issues. Choice of the above mentioned aspects is based on depth of coverage in academic literature.

Paper starts with introduction into SMEs and discusses the issue of financing gap associated with the sector in chapter 1. In chapter 2 it draws on features specific to the sector as well as those that differentiate small firms from the larger companies. Chapter proceeds with description and discussion of main modeling techniques and approaches used today in credit risk assessment of SMEs.

Chapter 3 of the study elaborates on issues that require attention not just during the statistical estimation of the model but also prior to that, such as, correctly identifying one's forecast horizon of interest and properly defining default that would suit the analysis and one's eventual goals and objectives. Aspects related to censoring and generation of dataset as well as types of determinants of default and aspects of their selection are discussed and analyzed here. In this chapter paper also attends to effects of credit risk measurement of SME loans on capital requirements for banks, main lender to the sector, and highlights findings of past research in the area.

Based on analysis of past research related to issues discussed in chapters 1, 2 and 3, chapter 4 concludes with findings and suggestions on optimal choice and approach to key aspects stated above. Chapter ends with suggestions on further scope of research in the area.

# Introduction

With credit decisions being defined as increasingly important and crucial decisions in today's business environment, affecting entire life-span of a business, failure results in high costs for firms, society and economy in general. We, thus, see evaluation of business failure as emerged scientific field seeking optimal prediction models, depending on specific characteristics of the firms studied.

The main job of a credit analyst is to determine risk relative to the portfolio one is analyzing. In such analysis quantitative factors are vital variables as they allow an expert to say whether a company with a certain, say, leverage ratio, is risky or not. Credit analysts of public large corporates are availed with sophisticated tools of measuring associated credit risk of their borrowers, which allows them to efficiently summarize substantial size of the analytical data, like financials, into standardized condensed number, probability or rating, that would rank a corporate effectively along the ladder of associated default probability and allow analyst to focus his expertise more productively and apply the subjective, expertise-driven, analysis to produce a verdict where it is needed the most.

Middle market lending, however, is still primarily a subjective process. No universal and objective benchmarks are existent up-to-date that could be applied across all Small and Medium Enterprises (SMEs) effectively and would allow their loans to be securitized. As market value information is valuable and not reflected in financials, private firms default models are sub-optimal to those companies with traded equity (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000). After many years of research, there is no universally accepted model for predicting probability of default (PD) for SMEs, based on causal specification of underlying economic factors. This contributes significantly to the financing gap that the SME sector is faced with. Lack of credit to this sector persists heavily despite the fact that SMEs are a major contributor to economy's output and development.

Importance of making an accurate judgment about counterparty's PD is high especially for financial institutions, like banks, whose margins on net cash flow are so narrow and their leverage is so high that small differences in actual and estimated assets' quality may affect their solvency substantially and, hence, solvency of financial sector of economy as a whole. The lack of precise methods in measuring of credit risk results into numerous problems for lenders: (i) high unexpected losses, (ii) high cost of credit applications review, (iii) frequently credit decision-making is separated from collection function, while the feedback from the latter is vital for development of judgmental skills in people who approve credit applications, (iv) lack of experienced personnel and due to lack of specific methods, personnel is hard to train. Each loan that is mispriced or mistakenly granted represents a lost opportunity. Hence, importance of better credit analysis should not be underestimated.

In light of the above, this study tries to focus on specifics of credit risk analysis of SMEs and discuss how the approach should be modified to incorporate these unique features of smaller companies.

# CHAPTER 1

## Definition of SMEs

SMEs are a diverse group of firms, mainly concentrated in trade, agricultural, manufacturing and service sectors of an economy. Almost every company started as an SME at some point of time.

Different countries use different criteria to define SMEs. Most commonly used criteria are employment and turnover. However, in cases where same criteria are used, definition of an SME is still not uniform across countries. In EU, for example, since January 1, 2005 enterprises qualify as small and medium-sized enterprises (SMEs) if they fulfill the criteria summarized in the table below. In addition to the staff headcount ceiling, enterprise as an SME should meet either the turnover or the balance sheet ceiling, but not necessarily both.

**Table 1: SME definition criteria in UK and EU[1] [2]**

| Region | Enterprise category | Headcount | Turnover | or | Balance sheet total |
|---|---|---|---|---|---|
| EU | Medium-sized | < 250 | ≤ € 50 million | | ≤ € 43 million |
| | Small | < 50 | ≤ € 10 million | | ≤ € 10 million |
| UK | Medium-sized | ≤ 250 | ≤ £ 25.9 million | | ≤ £ 12.9 million |
| | Small | ≤ 50 | ≤ £ 6.5 million | | ≤ £ 3.26 million |

In the UK, Companies Act of 2006 defines a SME mostly for the purpose of accounting requirements. While headcount ceilings are similar, turnover and balance sheet ranges are substantially different for the two regions. It is worth to note that even within the UK these definitions are not universally applied.

Many analysts came to agree that size of a company is a subjective feature and is relevant to a sector in which one operates: a company of a certain size can be classified as small in one sector, but viewed as large in another with fewer industry peers and smaller market. In the USA, the definition of small business is set by SBA (the Small Business Administration). The “size standard” terms are used to indicate the largest a firm can be in order to qualify as a small business, and therefore benefit from small business targeted funding. The subject entity cannot be dominant in its field, or on a national level. It should be independently owned and operated. Unlike the UK and the EU, which have simple definitions applied across all industries, the US defines a set of “size standards” for each individual industry. The variation is designed to better reflect industry specifics and differences. Some of the most common size standards are summarized in Table 2.

[1] (European Commision, 2010)
[2] (Small and Medium Sized Enterprises: Definition, 2011)

Table 2: SME definition criteria in US[3]

| Region | Enterprise category | Industry | Headcount | Turnover |
|---|---|---|---|---|
| US | Small | Manufacturing and mining industries | ≤ 500 | |
| | | Wholesale trade industries | ≤ 100 | |
| | | Retail and service industries | | ≤ $ 7 million |
| | | General & heavy construction industries | | ≤ $ 33.5 million |
| | | Special trade contractors | | ≤ $ 14 million |
| | | Agricultural industries | | ≤ $ 0.75 million |

## SMEs' contribution and role in the economy

Today, great share of many countries' GDP is produced by the SME sector, which also tends to be the main employer of most economies. SMEs are recognized as the main source of dynamism, innovation and flexibility in advanced industrialized sectors of the global economy.

For OECD countries, percentage of small and medium enterprises out of the total number of firms in the economy reaches 97%, who facilitate around 75% of all jobs and represent around 99.7% of all employers (Altman & Sabato, 2007). In US alone, in 1996 over 2.5 million of the total 4.5 million companies were characterized as small with assets less than USD100,000. Only 16,000 of those companies were rated as large corporate with assets value over USD100 million (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000).

Contribution of SME sector to GDP of several countries is summarized in Table 3. One can see that presence of SMEs in developed economies is substantial, making up for over a half of all companies in the economy. GDP input is at 50% mark for most of the countries with an exception of Sweden at 39%. Differences in importance of SME sector across countries are more notable between developing economies. While presence is remarkable at over 60% across central Europe, South America and South-east Asia, hiking over 70% in Argentina and Vietnam, GDP input is close to the levels of developed economies only for representative countries of South America and Poland, but only 27.3% in Turkey. Eastern Europe can be considered as a group with stand alone features where sector's presence and contribution to the GDP is around 10% and lower. Possible reasons could relate to inherited economy formations of the ex-Soviet Union countries, characterized by centralized power of government with high degree of nationalization of industries. Ayyagari et al. (2003) demonstrate importance of SME sector to rise with economic status of the country: SMEs contribution to employment (median values) increases from just over 30% for low income countries to over 60% for high income ones. For the same groups input into GDP (median values) hikes from 15% to over 50%, respectively.

[3] (Small and Medium Sized Enterprises: Definition, 2011)

Table 3: Contribution of SME sector to GDP[4]

| Economy | Nation | GDP/CAP, $ | SME/Total Firms, % | SME contribution to GDP, % |
|---|---|---|---|---|
| Developed | Canada | 19,946.50 | 58.58 | 57.20 |
| | United States | 28,232.07 | 52.54 | 48.00 |
| | United Kingdom | 19,360.55 | 56.42 | 51.45 |
| | France | 27,235.65 | 62.67 | 61.80 |
| | Germany | 30,239.82 | 70.36 | 42.50 |
| | Italy | 19,218.46 | 73.00 | 58.50 |
| | Sweden | 27,736.18 | 56.50 | 39.00 |
| | Japan | 42,520.01 | 74.13 | 56.42 |
| Developing | Belarus | 2,522.94 | 4.59 | 9.00 |
| | Russian Federation | 2,614.38 | 13.03 | 10.50 |
| | Poland | 3,391.08 | 61.81 | 48.73 |
| | Turkey | 2,864.80 | 61.05 | 27.30 |
| | Argentina | 7,483.77 | 70.18 | 53.65 |
| | Peru | 2,162.12 | 67.90 | 55.50 |
| | Philippines | 1,099.31 | 66.00 | 31.50 |
| | Vietnam | 278.36 | 74.20 | 24.00 |

As Berry (2007) highlights, an important challenge in many economies, especially in developing and economies in transition is to ensure that a significant part of output is produced outside the overly capital-intensive sector. Significant part of the SME sector's contribution to overall efficiency of an economy, employment generation and distributional wealth equality stems from the pattern of technology choice attributable to the sector. An economy with prevalent SME class can generate low level of inequality in income distribution as compared to the dualistic economy dominated by both, capital-intensive sector of large corporates and informal sector characterized by low capital use. This is true as jobs in informal or micro firms are often characterized by low productivity and hence low income, with the complete opposite being true for capital intensive firms. Feature of intermediary technology is what makes SME sector special when it comes to creation of adequate and sound employment. South Korea and Taiwan serve as good examples of the fact (Berry, 2007).

In addition, SMEs are an important source of innovation. They tend to dominate new and fast growing industries. Usually occupying specialized market niches, SME cater to small markets with products and services that large companies choose not to target. By following competitive strategies that differentiate them from other competitors, SMEs engineer products to meet market demands through innovative sales, distribution and servicing techniques.

The SME sector is also perceived to be a major driving force for competition and efficiency in an economy. Given the nature of markets served and capital-intensity of industries that SMEs operate in, companies need to be competitive to survive. Markets characterized by first-mover advantage see new

[4] (Ayyagari, Beck, & Demirgüç-Kunt, 2003)

entrants in the form of SMEs as the main source of price-lowering and quality-enhanced competition. This not only increases the output of industry but also enhances social welfare through reduced practices of monopoly/oligopoly/monopsony.

## Supporting SMEs

Enhancing performance and sustainability of SMEs can lead to growth of an economy. According to the International Finance Corporation, there exists a positive relationship between a country's overall level of income and the number of SMEs per 1,000 people (World Business Council for Sustainable Development, 2006). A healthy SME sector is a source of employment and income. It reduces wealth inequality among classes, leading to social stability. Unlike the informal sector of an economy, SME firms are a source of tax revenues to governments and social benefits to their employees.

Internationalization of business activities has progressively involved SMEs in global value chains. Large companies can improve their distribution networks and gain access to new markets through effective contracting of local SMEs, who have better understanding of domestic demands, have access to isolated regions, knowledge of local resources and purchasing trends. At the same time, access to global markets brings many opportunities to the SME sector itself. These would include access to new or larger markets, technological upgrade, and risk diversification through greater geographical coverage, lowering or sharing of costs, as well as easing access to credit.

However, the above is true for SMEs that do not face direct competition from foreign large companies entering into the market. For directly competing SMEs globalization does pose a threat. This is usually a scenario for industries characterized by economies-of-scale effects.

Many countries, especially those of OECD, strive to promote entrepreneurship and SME with various programs and policies targeted to combat such vital issues as financing, management, technology, information, R&D, etc. These can take form of privileged taxation and loan interest rates, award of contracts in certain areas exclusively to SME sector, access to informational data bases on exporters, suppliers and market reports, subsidizing strategic IT use, managerial and accounting training, support in participation in trade fairs, formation of networks and clusters within SME sector as well as with MNEs, securing e-commerce environment, and others (OECD, 2007).

## Financing gap in SMEs

SMEs need to adapt to changing economic conditions quickly and satisfy prevailing needs of economy. Available financing to exercise the available opportunity and to react quickly to changes in the market are therefore extremely vital aspects for SME operations. Despite the recognized importance of the sector, short supply of financial products and services for small and medium enterprises persists: Asian Banker (2005) reports that only 5% of world's 500 million low income firms have access to financial services (Dun & Bradstreet, 2006). Figure 1 describes SMEs' access to finance across the globe.

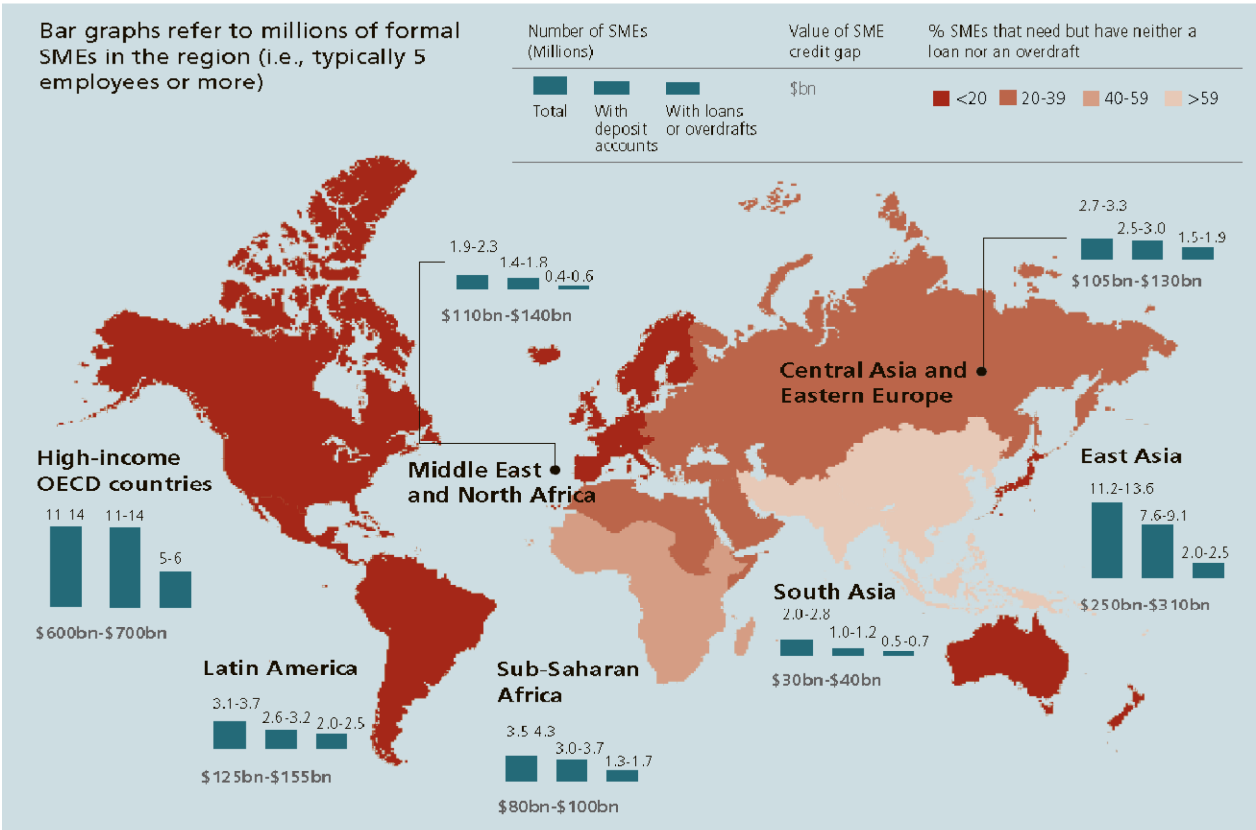


**Figure 1: Overview of formal SMEs' access to finance by region**[5]

Duns and Bradstreet (2006) highlight the following as major obstacles for SMEs' access to capital markets:

- lack of market credibility,
- poor historical performance,
- high transaction costs,
- perception of high risk associated with the sector

Among external factors, complicating the issue further, D&B stresses unfavorable regulatory environment, poor credit infrastructure, lack of access to advanced information and technology.

The increased attention to financing of SMEs has been raised with the view to evaluate the difficulties that these companies face, to promote adequate public support programs, facilitate efficient allocation of financial resources within the economy and assess SME abilities to service their debts. Smaller firms are sensitive to the state of the economy as they are less likely to benefit from scale effects; they possess little power when negotiating with financial institutions, and often operate on small markets. Due to lack of diversification and distinct product, SMEs are more uncertain about their future cash flow levels and timing, which results into inconsistent and volatile financial data. Due to undercapitalization and difficulties in access to mid-term credit lending, SMEs are characterized by high dependency on

[5] (IFC Advisory Services | Access to Finance, 2010)

short-term borrowing. While many SMEs unavoidably rely on such financing, their corresponding commitments are often of longer durations. Many governments and SME associations raised concerns that high capital charges for SMEs could lead to credit rationing of smaller companies. Leaving them without access to external funds means limiting investment capacity and therefore reducing scope and pace of productivity and technological advancement of global economy.

While alternative forms of financing, like trade credit, play an increasing role for SMEs, bank loan is still an extremely important tool of external financing for this sector of economy. This is so due to low levels of equity and preventively high costs of going public. SMEs are eventually much dependent on external financing, primarily, their relationship with local bank, which is often characterized by “relationship lending”. With competition in banking industry rising, such traditional ties are becoming less frequent and more difficult.

As OECD (2006) report notes, degree to which SME sector is isolated from external financing depends on how developed and competitive the banking and lending sector in an economy is: the more competitive it is, the more there are incentives for the lending institutions to overcome various difficulties to access the market. If the lending sector has alternatives to make required returns at lower risk, it will never develop tools to lend to SME sector without government intervention in the form of incentive policies (The SME Financing Gap, 2006). For lending institutions the cost of determining credit risk is often greater than the benefit in terms of cost avoidance, it is time consuming and expensive to extensively evaluate a credit application on individual level. Hence, the lending sector has little inclination to finance SMEs and the SMEs, in turn, have little incentive to operate transparently and keep producing proper accounting. However, given the vast majority of companies represented by SME segment and diversification across economic sectors, small business lending has a positive potential impact on bank profitability.

As mentioned earlier, there are alternatives to bank lending for financing of SMEs. Trade credit, i.e. credit supplied by non-financial firms, was always identified as one of the most important components of SME finance with many analysts arguing that the development of trade credit is crucial in assuring adequate financing to SME in emerging markets. Trade credit provided to SMEs allows stretching their accounts payables period. This, in turn, reduces cash conversion cycle of the company and provides scope for increase in sales. Latter could be achieved through the consecutive introduction of trade credit policy by SMEs themselves. Working capital and elements shaping it were found to be important factors contributing to growth of firm value. Michalski (2007) demonstrates through the use of Value-based and Portfolio Management Approaches how the company can add enterprise value through liberal trade credit policy.

Since SMEs are mostly unrated, most of the companies engaged in a business relationship with such firms are forced to rate and determine credit worthiness of counterparties internally. Banks and other lending institutions, mainly in the most advanced countries, invest heavily in reducing the costs of asymmetric information and, hence, risk of lending to the SME sector: producing credit scoring models and other sophisticated techniques that distinguish good borrowers from bad. Such tools allow creditors to identify the counterparties that are most likely to survive and, moreover, grow in the future, making it worthwhile to start a relationship with them.

# CHAPTER 2

## Sector-specific features

SME sector has distinctive features of business operations and corporate governance, which makes these companies increasingly different from large corporate in approach of risk assessment. Monitoring SME's adherence towards contractual obligations of loan contract is complicated due to reasons primarily related to the business nature and attributes of a small firm. In particular such companies are usually characterized by low survival rate and high volatility in profits and growth rate. For SMEs that manage to survive the start-up period, it takes time to establish sustainable revenue levels mainly due to unfamiliarity of clients with the new supplier in the market. At that stage, new small firms still have reputation and clients' trust to be gained. As a result, number of orders and, hence, profitability is volatile. Moreover, it is often the case that a new entrant company has to compromise between profitability margins and gaining new orders. Therefore, it is very unlikely that a bank would be willing to lend to a company younger than two-three years knowing that it is yet to pass the test of fittest.

Since the level of operations of smaller companies is low, contracts that they enter into are not publicly visible and are not covered by press. Moreover, contracts and suppliers are usually kept confidential in order to secure business for maximum possible time, since competition among smaller firms is fierce. By publicizing an income generating contract, an SME risks attracting competitors to counter-bid their offer and, thus, reduce their chances of securing the business.

Most SMEs are private firms owned by a single person or family-run. Thus, it is frequently observed that there is highly positive correlation between financial situation of the company and that of the owner. If the owner has scarce resources, there will be little equity to support firms operations at the outset and vice versa.

Additionally, most SMEs have poorly or minimum structured management. They are usually managed by very few directors who have great freedom of choice in actions and no corporate governance in place. In cases where SMEs are managed by respective owners, managers, owning total capital, seek to minimize penetration into their business in order to maintain total control not only over capital but over operations as well. This often leads to the company not being able to tackle several tasks simultaneously or dynamically expand in several directions as it could have otherwise.

Most importantly, accounting data of SMEs appears only at very discrete intervals, mainly on yearly basis and unaudited. As a result, SMEs are characterized with lower quality accounting. An important aspect of data quality relates to fraud and "cooking" of financial statements by the SMEs (European Federation of Accountants (FEE), 2005). This is largely due to fewer obligations related to data disclosure and reporting when it comes to smaller companies. And in cases where some information is available, interpretation of it is complicated due to the specific nature of the small enterprise. As a result, SMEs cannot credibly convey their quality, hence, their loans are illiquid.

From the above, it is clear that SMEs are opaque, volatile and more specific to internal shocks. Such lack of data and informational opacity make the area of SME credit risk modeling under-researched. Plus, loans provided to them are usually of smaller size, making average cost of lending to an SME relatively high, as lenders face fixed cost of lending. There is also an extensive variation in the legal structures of SMEs and their activities, which further complicates the issue of establishing homogeneity in credit risk assessment of SMEs. Their liability is largely determined by the legal form of the business entity. With private persons being fully liable for their losses, owners of SMEs can limit their liability more easily by incorporating the firm as a legal body with a limited liability (Fidrmuc & Hainz, 2009).

## Credit risk perspective: SMEs vs. Large Corporates

There are many countries that virtually have no traded firms and are highly characterized by SME sector. While private firm debt is perceived by the public as at least as risky as public firm non-investment grade debt, in reality, it is likely less so. Altman et al. (2007) show that SMEs are riskier than large corporate in terms of firm-specific risks and, therefore, require their credit risk to be addressed separately, in order for lenders to have a clear picture and valid estimates about expected losses (Altman & Sabato, 2007). Advocating similar argument, Jacobson et al. (2005) note, while being more exposed to a firm-specific risk, SMEs are less vulnerable to a systematic, or market/contagion risk (Jacobson, Linde, & Roszbach, 2005). Although smaller companies can be associated with higher expected loss levels as compared to large corporate firms, for unexpected losses, lower levels are associated with smaller firms rather than large ones mainly due to lower default correlations between the smaller firms. In general, defaults among large firms are thought to be primarily caused by systematic risk factors.

Founders of KMV model came up with the idea to regress default probabilities derived from market based model on accounting factors for companies belonging to particular sector and region and then use those estimates in prediction of default probability for smaller firms. Sobehart et al. (2000) showed that relationship between financial ratios and credit risk varies significantly among big public and small non-traded companies, suggesting that default models based on data from traded companies and applied to probability of default prediction of smaller ones will tend to misrepresent the true relationship (Sobehart, Keenan, & Stein, 2000).

Falkenstein et al. (2000) suggest that differences between public and private companies are reflected in differences in distributions of ratios rather than their absolute values. For example, leverage ratio is usually higher for public firms than it is for private. However, Falkenstein shows that historical distribution of liabilities over assets has a fat tail when L/A greater than 1. This is true for 10% of private firms compared to 8% of public, characterizing companies with negative net-worth (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000).

Above shows that credit risk assessment models applied to large companies are not suitable to those of smaller size. This is so because unique features of SMEs transform into different patterns in financial ratios and indicators that once used in models estimated for larger companies will tend to misrepresent the true credit risk of a small company. Plus, the factors that exert greatest influence on continuity of business operations for smaller firms are more internal in nature as compared to big companies.

## Credit risk assessment models

While the availability of academic literature on credit risk assessment and modeling, both theoretical and practical, is vast, little was devoted to the smaller, non-listed companies. While in theory the differences between the two are known, the main problem lies in the lack of data on smaller firms required for carrying out a credible research. Optimal model, highlighting important determinants of critical factors affecting default probability of the smaller companies is, therefore, absent.

In general, there are three main types of models of default prediction, distinguished in credit research literature:

- Expert judgment models
- Statistical models (NN, DA, logit, probit, etc)
- Hybrid models

In the following sections I shall give an overview of the above groups of models, highlighting main advantages and disadvantages associated with each. Hybrid models are those models that compromise between expert and statistical models.

### Expert judgment models

Expert judgment or expert-rule based models prevail in today's commercial analysis. This approach stresses importance of qualitative data, however, quantitative information is also used. Users of judgment approach tend to prefer former type of information to latter, since the second one is often difficult to obtain and, even, if available differs significantly across industries and sectors, thus, requiring a proper industry benchmark.

Judgmental models are guided mainly by credit expert's experience with the company, type of product the company sells and industry it operates in. Such models have little or no statistical base, although they are mostly mapped against real industry financial profiles.

There is no doubt which of qualitative or quantitative model is more cheaper, faster and consistent, but superiority of latter is only feasible in cases where it does not worth to analyze loans individually like is the case in consumer credit. In contrary cases of complex derivative data, expert is preferred. Can a model based on large default-observation sample outperform an average analyst? There are several biases, which point to inherent flaws of expert system, stemming from behavioral finance. These are highlighted in the work of Falkenstein et al. (2000). In particular, people tend to overestimate the precision of their knowledge: highlighted research of Libby (1975) shows that while experts were correct in prediction of default 74% of the time, a simple ratio of liability/assets outperformed analysts (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000). As Latimer Asch, ex-vice-president of Fair, Isaac and Co. Inc. mentioned: "Although the human mind is a wonderful thing, it can really handle the interaction effects between a couple of different variables and not necessarily well. Unless you do the full empirical statistical analysis, you really cannot do a correlation analysis" (Schmidt, 1998). It is therefore, important to understand that judgmental and statistical models are complimentary rather than competing tools. The key is for the expertise of an analyst to concentrate more on areas where it adds the most value, thus leaving the ultimate competitive advantage with judgmental process.

## Statistical models

Opposed to approach of Judgmental models is the one of statistical modeling, which advocates superiority of quantitative data in establishing underlying causal relationship between the probability of default and cause factors. Statistical models are governed by statistical methods, considering many factors simultaneously, thus calculating and analyzing multivariate correlation in order to identify most powerful factors and produce statistically derived weights to be used in consequent scoring model.

Use of statistical models in collection process advocates the emphasis placed on inherent risk characteristic of the borrower as opposed to aging items. Why is statistical model preferential to judgmental in such a case? Reason is that the latter informs on quality of the risk separating lowest risk accounts from highest ones, while statistical model quantifies the risk by informing you on the probability of default and, therefore, associated expected loss, i.e. value of the risk (Driving Internal Collection Results With Statistical-based Credit Scoring, 2010).

One of the most important and prominent contributions made to the field was the observation by Beaver (1967) that there are several financial ratios, which differ significantly between failed and non-failed firms, in particular cash flow/net worth and debt/net worth (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000). In short, differences in such ratios for viable and bankrupt companies increase as time to default shortens – as failure neared, firms became more dissimilar.

One step further was taken by Altman (1968), who reasoned it optimal to create a multivariate model with several such important explanatory variables that had low correlation as compared to a single variable model in predicting solvency of a firm. Quantitative data does not do the work if is used as individual ratios, as that would constrain the analyst to compare the stats sequentially and likely end up with ambiguous result. Multivariate model is therefore useful tool in this field. Altman was the first one to use a statistical model to predict default probabilities of companies, estimating the Z-score model through the application of discriminant analysis, which subsequently underwent several refinements and became a benchmark in academic literature. Although popular, Z-score failed to establish itself as the ultimate tool in determining credit quality of a borrower. Reason is that the model does not perform well, scoring roughly equivalent to a simple univariate ratio benchmark as liabilities/assets (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000).

Another prominent model among statistical apart from Z-score is Merton's. However, it is inapplicable to SMEs as it uses traded equity prices - data which is not available for private firms.

There is an extensive line-up of statistical models. One of them is Discriminant Analysis (DA). Main pitfall of the model is that its basic assumptions are generally violated when applied to PD modeling, like homoskedasticity and normality. Plus, standardized coefficients cannot be interpreted as the slopes of the regression equation and, thus, do not reflect the relative power among regressors. Logit models, on the other hand, fit well into the scenario of PD modeling. Here dependent variable is binary, accommodates disproportional samples and does not require the restrictive assumptions of the DA. Scores produced by this regression model can be conveniently interpreted as PDs. Also, each of the coefficients can be interpreted individually stating relative importance of each regressor in explaining variation in the dependent variable (Altman & Sabato, 2007).

Suggested by existing research (Falkenstein et al. (2000), Hayden (2002), Fantazzini et al. (2009), for example), probit and logit estimators are preferred over those of DA. Choice between two former models is less important as both usually yield similar results (Fantazzini et al. (2009), Hayden (2003), for example). While DA separates default from non-default observations, probit and logit interpret which observation has a higher probability of belonging to a certain group, which makes latter forms better equipped to produce PD that could also be used for expected loss estimation. The bottom line is: DA states that differences among the approved credits are not due to differing characteristics but due to noise from their estimation. Nonetheless, both, DA and logistic regression have been the most widely used methods for constructing scoring models for SMEs.

Among other statistical models gaining popularity are Neural Network models. While some studies suggest that neural networks can outperform probit and logit models in achieving higher accuracy ratios (see Coakley and Brown (2000), Bensic (2005)), others prove that differences are marginal or virtually non-existent (see Hayden (2003), Huang et al. (2005)). Moreover, probit and logit models allow to check whether the empirical dependence between the potential input variables and default is economically meaningful, while NN don't (Hayden, Are Credit Scoring Models Sensitive With Respect to Default Definitions? Evidence from the Austrian Market, 2003). Neural network approach, in general, leads to multimodal optimization problems having no numerical stability properties of concave maximization problems that exist with logit, probit and Maximum Expected Utility approaches (Friedman, Huang, Servigny, & Salinas, 2003). Although NN has been reported as a good performance methodology, it classifies objects by its computational characteristic in a "black box" manner, lacking transparency (Lin, Wang, Wu, & Chuang, 2008).

### *Structural and reduced-form models*

Models can be structural and reduced form. Former is introduced by Black and Scholes (1973), Merton (1974) and latter is originated with Jarrow and Turnbull (1992). While structural depend on the underlying logic or theory, reduced-form models are dictated by the patterns that any given data subset exhibits. People tend to prefer former to latter, as it provides them with intuitive reasoning behind the structure of the model, implying that certain relationship should hold irrespective of the behavior of data.

While the two are competing, they are not as disconnected as might seem. Jarrow and Protter (2004) show that (Jarrow & Protter, 2004), the main distinction lies in information set available to modeler as assumed by the two types of models: structural models assume complete knowledge of detailed information set, i.e. both, firm's assets and liabilities values. Reduced form models, on the other hand, require less detailed information about the firm's assets and liabilities than the structural models do. In fact, structural model assumes that information available to the modeler is same that is available to the managers of the firms, whereas reduced form assumes that modeler is availed with the same information set that is observable by the market.

What model is preferential depends on the eventual use of the model. In measuring a company's default risk, structural model would be preferred due to assumed complete information that would provide more accurate estimates.

## Hybrid models

### *Credit rating models*

Credit ratings reflect both qualitative and quantitative data in form of opinion based on extensive human research of company's performance. Despite recent criticism and the role that ratings have played in the recent recession, they remain to be widely used and most common measure of credit quality. Most of the corporate executives today analyze the effectiveness of corporate strategies and policies based on the implications that the latter may have on their corporate credit ratings. Recent crisis underlines the importance of understanding whether credit rating agencies should be relied on and produce appropriate metrics for these purposes. Hilscher et al. (2010) view rating as puzzling measure of credit risk for a number of reasons: (i) they can be easily improved upon by incorporating publicly available information into the credit scoring model, (ii) they fail to differentiate between the firms and (iii) they fail to capture the variation in default probability over time. Paper finds that credit ratings reflect variations in systematic risk and not in overall credit quality of the borrower (Hilscher & Wilson, 2010).

### *Credit scoring models*

Credit scoring models evaluate credit risk based on statistical analysis of historical relationships between credit defaults and certain characteristics of borrowers. The basic idea behind a scoring model is that if the applicant resembles borrowers that performed well in the past, then it is likely to fulfill the obligations as well. It uses numerical relationship to predict the credit quality of the borrower, based on the information obtained from applicant himself or credit rating agency. Based on the historical relationship, weights are assigned to each characteristic factor that is seen to be influential. Products are summed to result in a score that grades the borrower on a certain ladder of credit worthiness. "Black box effects" can be avoided by passing the result of credit scoring model through to a credit expert (The SME Financing Gap, 2006). The reliability of the scoring model depends on the accuracy, completeness and timeliness of the information used to estimate the model, as well as on the stability of population.

Commercial banks and credit card companies were the first companies to use credit scoring models. Retail sector has seen credit bureaus' scoring evolve dramatically and rapidly with their scores today capturing up to 90% of the measurable risk inherent in consumer relationship (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000). However, information required to adequately assess credit risk of a business is far more comprehensive and costly, can vary substantially in availability and is more difficult to validate and analyze than that of an individual.

Paper by OECD (2006) reports that credit scoring in US was associated with increased lending to small business sector. However, this was seen to be more a result of reduced cost rather than reduced information opacity.

Benefits of credit scoring include:

- speed – through the use of automated system, every customer can be evaluated faster
- consistency and accuracy – since same evaluation rules apply to all clients, consistency prevails throughout the company
- reduced bad debt losses – high-risk customers are identified as exceptions and are reviewed by experts; orders are not approved by the virtue of a simple rule where requested credit is below a specified threshold; through quick identification of problematic customers that require attention, shipments can be held and cargo kept on lien that otherwise would be processed
- reduced personnel costs – with companies having numerous customers and relatively low amounts per transaction, credit scoring can have substantial impact on reduction on cost of labor required to process a credit limit application; with automated system, less labor force is required to research, check references and make decisions
- prioritization of collective actions – credit scoring facilitates specialization of collection strategies with regard to credit profile of a borrower, once credit score and o/s amounts are combined
- decision support and planning tools – credit scoring models allow one to adequately assess and report the quality of the overall portfolio of account receivables (Rules Based Credit Scoring Methodology, 1999)

As the above suggests, credit scoring leads to enhanced operational efficiency and hence, to reduced operational risk. This fact boosts the importance of the tool within risk management practice even more.

Credit scoring models should be recognized as supporting tools enhanced by judgmental model for the greater integration of information, especially "outside the model" one, so that more sophisticated refinements of any single score can be made in a more disciplined manner – a point repeatedly highlighted throughout the paper to stress the importance of the argument.

Risk assessment models are required in order to judge effectively the repayment capability of the debtor and lending institutions, be it banks providing loan, manufacturers or trade enterprises providing trade credit, require these to secure collection from their debtors. Credit scoring today is becoming more and more powerful tool in automation of credit risk analysis and collection of the company's accounts receivables portfolio, with largest assets on most companies' balance sheet. One of the main reasons behind it is rapid technological advancement. As report by Sunguard (2009) states, till today, in most of companies' credit control departments, collections are prioritized on aging: customer owing the most money for the longest period of time receives most attention in collection process. 25% of companies that use credit scoring for risk analysis also employ it in collections process, against 21% in 2003. On average, just 10% of the credit department's time is spent on credit risk analysis and 90% devoted to collection of outstanding (Driving Internal Collection Results With Statistical-based Credit Scoring, 2010). Report infers that using only aging in prioritizing collection can often result in wrong treatment directed at wrong customer at the wrong time, with high risk low exposure-at-risk accounts being neglected due to primary focus on high exposure-at-risk borrowers (Driving Internal Collection Results With Statistical-based Credit Scoring, 2010).

The power of scoring mode is maximized when used in combination with Performance Management Table (PMT), which provides a comprehensive picture of expected risk distribution of existing credit portfolio. It also allows the credit manager to identify the acceptable level of risk that the company is able to tolerate given its running exposure (Banasiak & Tantum, 1999).

## Conclusion

There are many models available today at the disposal of credit risk managers, but all are bound by one limitation: model provides one with a credit score, rating or an estimate of PD for a client, thus assessing the risk, based on historical patterns, but it can never predict unexpected real world situations, for example, a sudden downturn in a particular industry or economy, or change in the company's management. Essentially, the sooner a model predicts default prior to equity value reaching nil, the more value it adds. This means that optimal model should put more emphasis on factors that tend to deteriorate more at some intermediary point in the future prior to default rather than studying factors that plummet right before the event (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000). In other words, the thing that eventually determines long run viability of a model is its real-out-of-sample performance.

Models not optimally specified, but which use best normalized inputs, are often as good in predicting PD as statistically estimated models, especially given acceptable positive correlation among regressors. Falkenstein finds in his study that improper model performs better than 3-variable Shumway's model, followed by Z-score and simple ratio, in respective order, when estimating 5-year PD for private firms (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000). It is therefore hypothesized that a reduced form credit scoring model, augmented by credit expert review to account for factors not incorporated in the model, is preferential for assessment of credit risk of SMEs. In addition, it provides a quantifiable measure of credit risk that can be effectively communicated to management and throughout the companies via reporting of changes and shift of credit portfolio not just on individual basis but also on the overall loan portfolio or/and level of accounts receivable.

# CHAPTER 3

## Choice of rating philosophy and time horizon

Since SMEs are mostly unrated, most of the companies engaged in a business relationship with such firms are forced to rate and determine credit worthiness of counterparties internally. Many companies have big difficulties in properly establishing credible and reliable estimates of their counterparties' risk when providing them with credit facility.

Credit risk assessment models can be used for many purposes. These include credit approval, portfolio monitoring, early warning systems, commercial activities, pricing of the credit facility, regulatory capital requirements, economic capital requirements, capital planning. Therefore, when developing a credit assessment model it is important to understand what the eventual use and application of the credit model will be and, hence, what kind of information one wants the score to summarize. As Rikkers and Thiebbueault (2007) suggest, this requires establishing of suitable rating philosophy. Without that it would be difficult to interpret the results of model.

As per Rikkers' definition, rating philosophy is how lender's grade assignments are influenced by the lender's choice of economic, business and industry factors, considered in the process of rating, over a particular time frame (Rikkers & Thiebbueault, 2007). Authors note that correct philosophy is essential as it influences design of the model, hence the system of credit risk assessment and its eventual applicability. Its importance is reflected in impact it has on such issues, like power of internal scoring model, warning signals of default, evaluation of loss given default and expected loss, rating and/or PD volatility, model validation and stress-testing, pricing of the credit facility. It is a trade-off between:

- Quality: do the grades produce a correct indication of PD
- Timeliness: are the grades based on the current position of the company
- Volatility: how often do companies migrate among the grades (Rikkers & Thiebbueault, 2007)

Thus, results produced by a model set with a wrong philosophy will be misleading. It is, therefore, important to differentiate between the horizon over which one seeks the model to characterize the counterparty: in point-in-time scores (PIT), risks are evaluated based on the current economic condition of a borrower irrespective of the phase of business cycle at the time of evaluation; through-the-cycle (TTC) approach looks less at temporary changes in the risk factors and concentrates more on financial health and ability of the borrower to survive through the economic cycle. The more volatile the company is, the shorter should be the applicable time horizon.

Rikkers and Thiebbueault (2007) describe the two approaches in their paper in great detail. PIT aims to forecast probability of default over a set period of time, say one year. Under a pure PIT system, risk grade will change as soon as borrower's condition changes, i.e. as soon as new information on it is released into the market. Thus, PDs under PIT reflect the forward looking default likelihood, based on the best available information on borrower's credit quality in the market. PIT is, therefore, defined by volatile credit scores, but constant probability of default per score. The higher the probability of default, the shorter the rating horizon should be, in order to track changes in PD of high risk clients quicker (Rikkers & Thiebbueault, 2007).

TTC, on the other hand, is the measure of ability of an obligor to remain solvent through the economic cycle and during severe stress events. That is, PD is estimated at the bottom of business cycle and under stress. Unlike PIT, TTC produces ratings that do not migrate with cyclical movements, but only due to changes in personal position of the borrower. TTC scoring, therefore, responds only to permanent shocks to the firm, transitory shocks are left out. Thus, TTC is defined by stable ratings, but PD associated with every rating may change over the cycle. That, in turn, makes the validation of such models more complicated as compared to PIT. Most of today's rating agencies follow the TTC system (Rikkers & Thiebbueault, 2007).

As noted above, PIT systems tend to have scores that migrate more frequently, while TTC see theirs shift more slowly as economic conditions change. This is particularly important for banks as they are subject to bank regulations of Basel II and, recently, Basel III. If PIT is adopted and credit scores change frequently, so would the associated regulatory capital charges. This would require bank to have sufficient reserves and tools at their disposal to accommodate such frequent and drastic changes. Such choice of system is a challenge to a bank as it leaves it vulnerable to shocks in the levels of minimum required capital to be maintained, higher probability to face regulatory penalties in the times of rapid slowdowns of economy. There is a certain advantage to that, however: it keeps the banks more informed of current developments and changes undergoing in the economy and concerned sectors, providing them with early signals, which eventually can make them more prepared to approaching recession and reduce potential losses as compared to the banks opting for TTC systems. Thus, during the slowdown or recession the horizon should be shorter than during recovery and boom. Moreover, as Rikkers states in her paper, PIT systems within banking industry can lead to credit crunch in recession due to increased and maintained capital requirements as directed by credit scores. TTC, on the other hand, have a more stable effect on capital requirements, hence, available funds, and therefore credit to the economy (Rikkers & Thiebbueault, 2007). It is also important to note that in light of recent events and credit crisis, business society is concerned about risk management as never before. Capital requirements can be considered to be applicable and useful not only to the banks, but to non-financial firms as a tool of enterprise risk management and means of cushioning their risk exposure in line with economic developments.

PIT has a cost advantage over TTC, as requires less effort in complex statistical analysis, which entails heavy costs. This is true for TTC as it requires more data to handle differences in industries and separating cyclical influences from secular, systematic from idiosyncratic factors. Geographical diversification of the credit portfolio can reduce the impact of cyclicality of a portfolio.

Neither of the two exists in its pure form. There are many important reasons to that, these include asymmetry of information, lack of sufficiently forward looking data, exact break-down of business, economic or industry cycle is extremely difficult, if not impossible (Rikkers & Thiebbueault, 2007). As a result, hybrid model is often the choice. Under hybrid model only substantial changes in the creditworthiness of the borrower are considered and short-term fluctuations, as the ones considered under PIT system, are usually ignored.

Type I error is often the case for TTC: some of the risky clients remain unnoticed as actual creditworthiness is ignored in the score. Under PIT, on another hand, there is a risk of Type II error, i.e. that a company is wrongly perceived to be risky, as all of current information is included.

In deciding whether to approve a credit facility, important question to be asked is whether the subject industry is located at its peak or the bottom of the economic cycle. PIT would be more suitable in this a case, as it indicates the current creditworthiness of the obligors. As Hilscher and Wilson point out in their paper, an investor may not only care about the raw probability (PIT) of the borrower to default but also about the tendency to default on times of bad economic conditions (TTC), i.e. about the systematic risk (Hilscher & Wilson, 2010). TTC is more concerned with longer-term viewpoint, which is of interest when decision on credit allocation is to be made. Since most of research revolves around PD for 1 year horizon, such alternative is often difficult to estimate. Firstly, generalization of one-year estimate over five years is likely to misrepresent the true probability as relationship between ratios and PD changes with time, and secondly, because of data scarcity for default observations over such long periods.

## Definition of default

Most of the models are concerned with estimating probability of default of counterparty over a specific time horizon, where default means not receiving interest and principal as specified in the debt agreement. Basel II defines PD as probability that a borrower meets the default definition within one year, expressed as a percentage. A default is considered to have occurred when either or both of the following events have taken place:

- "The obligor is 90 days past due on any material credit obligation to the banking group;
- The obligor is unlikely to pay its credit obligations to the banking group" (Basel Committee on Banking Supervision, 2006).

Probability of default can be either stressed or unstressed, where the former indicates likelihood of default, assuming adverse stress scenario of economic conditions, while the latter gives an unbiased estimate of the same. First case is attributable to TTC system, whereas the latter is a feature of PIT approach, as we learned in the previous section.

As per FSA, there is a tendency among firms no to use the complete definition of the default as set out by CRD. More specifically, firms are more inclined to limit the default definition to days over-due and not include the required "unlikely to pay" condition. Financial Services Authority expects the limited definition to produce higher capital requirements in cases of retail. As stated above in Basel definition of default, there are two dimensions – unlikely to pay leg and days-over-due leg. The shorter you set the definition in terms of latter leg, the higher will be the PD. Regulatory body also stressed the importance of "Missing defaults" issue, which can take the form of unrecorded defaults (which could be a result of weaker definition of default), not yet recorded defaults, omitted defaults as a result of deliberate policy action, data inefficiency of data is collected externally. The effect of missing defaults is to reduce PD and therefore capital requirements. The paper argues that "early versus late" aspect of definition of default is much more important than missing defaults. The earlier the credit facility is classified as non-performing or defaulted, the sooner it would be brought up to attention of collection department and certain actions will be taken (Financial Services Authority, 2007).

Different studies on the subject considered different definitions of default. There seems to be no clear cut agreement on the concept. For example, definition of default used in the study of Hilscher and Wilson is when either bankruptcy filing, de-listing or government-led bailout occurs. In study of Hayden et al. (2009) probability of default is defined as an observation when a firm formally applies for permission to miss an interest payment. Beaver, in his yearly research on multivariate regression analysis of credit scoring, defines failure as a business defaulting on interest payments on its debt, overdrawing its bank account, or declaring bankruptcy. Blum and Vallini et al. (2008), in their own respective studies, define failure as entrance into a formal legal bankruptcy proceeding for debt (bankruptcy, liquidation, etc.) or an explicit agreement with creditors that reduces the debt of the company. Falkenstein et al. (2000), in turn, applies a broad definition, using the following criteria on a loan to identify default:

- 90 days overdue
- Credit written down

- Classified as non-accrual
- Declared bankruptcy

First common feature to note with all above mentioned definitions is the diverse and broad dimensionality applied. One reason could be seen as an attempt by the researchers to avoid exclusion of any default observation from the sample available. Issue referred to as “missing defaults” by FSA. Data on default rates is scarce and to generate a large enough pool of default observations to carry out a meaningful research requires decades. Introduction of overdue leg in Basel II definition of default and inclusion of the criteria in research paper of Falkenstein, drives up the number of default observations significantly. In fact, this is exactly the feature of the data sample used by Falkenstein et al. (2000) that is highly emphasized and stated to distinguish their research from the ones of the past, where the pools of default observations hardly exceeded 50. But, how reliable is the definition with inclusion of over-due leg? While it is definitely a sign of concern that debtor may be experiencing difficulties with settlement, there are many cases where a debtor exhibits a payment pattern with average overdue period beyond 90 days, but nonetheless, never goes bankrupt. This is frequently the case in trade credit, where debtor’s payables are outsourced and processing time lag is substantial.

Another common feature of above mentioned default definitions is that most of them are based on explicit or official declaration of bankruptcy, either in the form of re-structuring, liquidation or formal legal bankruptcy proceeding. Once official declaration of default is made, it is least likely for all creditors to receive full compensation, even if liquidation is to take place and absolute priority rule to apply. The whole purpose of the credit risk assessment is to spot the deterioration of credit quality or financial health of a debtor prior to the actual default in order to take preliminary actions and enforce damage controls. Model based on such definition of default will bring no value in case of SMEs, whose liability is often limited.

While the first point criticizes the “too-early” definition of default, second highlights the obvious drawbacks of the “too-late”. So which one is optimal? In her study, Hayden (2003) tests the importance of definition of PD, where authors use the data of Austrian SMEs to construct credit scoring models using three different definitions of default: bankruptcy, restructuring, and delay in payment (90-days past-due). Study raises the question whether the structure and the performance of the credit scoring models is sensitive to the default definitions that were used to estimate them. In-sample and out-of-sample fit of the model with bankruptcy definition of default is found to exert similar and significant accuracy ratios (AR) of 60% and 59%, respectively (Hayden, Are Credit Scoring Models Sensitive With Respect to Default Definitions? Evidence from the Austrian Market, 2003). AR measure of power should be considered in comparison of models estimated from the same data set, as differences such as relative amount of defaulters to non-defaulters in the sample drive this figure substantially. The same finding is true for the other two definitions of default. Another interesting result is that three models estimated are very similar in their composition of regressors, implying that model derived for one definition of default can be used to predict differently defined default events. In testing that, authors apply the model derived from the bankruptcy defined default to the samples used for estimation of two models with other definitions and conclude that accuracy ratio decreases but only marginally, with difference being statistically insignificant and confidence intervals heavily overlapping for the three sample sets. Research concludes difference in definitions have insignificant impact on changes in corresponding capital requirements. The results are seen to be of special interest and value to the smaller banks and lending institutions due to their limited number of clients and substantial obstacles in collecting data required to update their credit scores (Hayden, Are Credit Scoring Models Sensitive With Respect to Default Definitions? Evidence from the Austrian Market, 2003).

## Determinants of default

Selection of variables and their transformation to yield a better fit of the model is a crucial part of the analysis. There are three main categories of regressors that can be used: accounting variables, market based variables (market equity) and soft facts like competitive position of the company in the market of management skills. Market based variables are not applicable as small enterprises do not have any market equity. That leaves us with accounting, or quantitative, and qualitative factors. Financial ratios are among the most prominent accounting variables that are used for SME credit scoring. However, availability of such data is restricted by availability of SMEs' financial statements. As report of Sunguard (2010) suggests, in building statistical model the most important variable is the internal accounts receivables data of the company, i.e. the payment experience observed (Driving Internal Collection Results With Statistical-based Credit Scoring, 2010). The advantage is further augmented by the fact that the information used does not cost anything to the company. It was found that accounts receivables data combined with credit rating agency report in statistical model is likely to increase the predictive power of the model by 5-10%. On the other hand, using only accounts receivables in a scoring model sees predictive power to rise by 10-200% over a model that utilizes just the credit rating report, plus, it costs much less (Driving Internal Collection Results With Statistical-based Credit Scoring, 2010). The questing arises: is the additional power worth the cost of such report?

We shall discuss each category in the following sub-sections separately.

### Qualitative variables

Most qualitative variables, like management quality and industry variation, are often left as unaddressed factors due to difficulty in consistent measurement and insufficiency of data for the model. Nonetheless, their importance in credit assessment of SMEs is highly stressed by many authors, who have tried to incorporate such factors in their models through the use of dummy variables.

Importance of industry specifics has been highlighted by many papers, including the work of Edmister of 1972. Five out of seven variables in model he tested employ industry average, highlighting the importance of industry specifics (Edmister, 1972). Fidrmuc and Hainz (2000), in turn, show that default rates differ substantially among industries, with higher than average observed in service and agricultural sectors of economy. At the same time, they find that credit allocation among different economic sectors is uneven, with a higher indebtness observed in sectors with high fixed assets value: in their study, industrial sector, represented by 15% of all firms, received 1/3 of all credits and agro industrial sector obtained 25% of all credits having just less than 6% of all firms represented by the sector. As a result less of credit is ration into the sectors with higher probability of default, like services sectors (Fidrmuc & Hainz, 2009).

Fantazzini et al (2009) highlight the presence of qualitative idiosyncrasies, like quality of management and business characteristics as important factors in explaining why one company defaults and another continues to serve its debt, while exhibiting similar financial fundamentals and debt structures (Fantazzini, De Giuli, Figini, & Giudici, 2009).

Analyzing dataset of SME loan applications and loan contracts of AccessBank in Azerbaijan, Berg and Kirschenmann (2010) make a heavy use of qualitative variables in their LPM estimation. Their study produces some important findings: crisis has a negative impact on credit approval rates, by 3.8% lower on average. The impact is even more drastic once compared separately between the industries: agro loan applications have a 9.7% higher chance of approval as compared to other SME loans for the pre-crisis period. After crisis the figure rises to 18% (Berg & Kirschenmann, 2010).

Interestingly, financial crisis influences denomination of loan considerably. For smaller firms, like agro and micro firms, bank tries to channel lending in such a manner as to ease the foreign currency exposure of debtors, and thus, make their repayment more likely than if it would be otherwise, especially in recession period, when domestic currency runs high risk of devaluation. Risk is further augmented if the country of operations is developing, where local currency is exposed to potentially high fluctuations. For bigger companies among SMEs, however, due to relatively larger amounts of loans requested and higher general exposure overall, bank has an incentive to lend in foreign currency to prevent currency mismatches on its own balance sheet, especially if it receives funding in foreign currency itself (Berg & Kirschenmann, 2010).

Supporting the argument of relationship lending, study found bank relationship to be a very valuable factor in receiving a credit facility: chance of getting your loan approved if you have an existing relationship with the bank is, on average, 5.7% higher than otherwise (Berg & Kirschenmann, 2010).

Collateral increases the probability of receiving approval since pledge security makes the exposure less risky as in times of default it can be sold against provided facility. Research of Berg and Kirshenmann (2010) finds that SME loans exhibit higher loan requested amount after Lehman's collapse, while at the same time being more collateralized due to higher perceived risk associated with SMEs (Berg & Kirschenmann, 2010).

Hayden et al. (2003) in their own study incorporate such factors like size, sector and legal form through the use of dummy variables. They find that in contrast to previous findings, size of the company and sector in which it operates are insignificant predictors of default, while legal form is proved to exert substantial explanatory power: companies with limited liability legal form are found to be associated with higher PDs than those with unlimited liability (Hayden, Are Credit Scoring Models Sensitive With Respect to Default Definitions? Evidence from the Austrian Market, 2003). Fidrmuc and Hainz (2009), in turn, show that lower default rates are found for natural persons as compared to legal bodies. Debtor's liability is largely determined by the legal form of the business entity. Private persons are fully liable for their losses. Owners, however, can limit their liability more easily by incorporating the firm as a legal body with a limited liability (Fidrmuc & Hainz, 2009).

Fidrmuc and Hainz (2009) state that firms are more likely to default if legal systems do not create efficient incentives to induce repayment. They highlight the existence of so-called "observed-risk hypothesis" where lender can observe company's risk ex-ante and adjust terms of credit facility accordingly. Thus, higher indebted firms would have higher proportion of their pay-offs to be paid off as interest expenses for the provided credit facility. This reduces the difference between the pay-offs from the success and failure projects for the firms and thus introduces incentives to make riskier investments. This moral hazard behavior decreases the probability of success and, hence, increases the probability of default (Fidrmuc & Hainz, 2009).

Authors go further to note that if the firm is legally fully liable, the investment decisions are internalized in the pay-off from the projects. For the opposite type of borrower, limited set of assets that are available for use as collateral for the credit facility (which could be liquidated in event of failure) prompts the debtor to repay only in the event of success. As a result, incentives are distorted. This argument applies to the strategic default, observed in many cases of SMEs. If creditor cannot observe perfectly the outcome of the project, debtor can claim the project to be a failure and retain the profits. In scenario like this, more liable the borrower, less incentives there are for the strategic defaults (Fidrmuc & Hainz, 2009).

Bensic et al. (2002) find features of transitional economies, like political, institutional and social deficiencies to play a major role. Small business development in transitional economies, as reported by them, is characterized by difficult access to turnover capital due to legal and law limitations, undeveloped infrastructure, high transaction costs, and high interest rates (Bensic, Sarlija, & Zekic-Susac, 2005).

It is also important to account for the geographical applicability of the data on hand, as it would incorporate dissimilarities that firms face in their endowments such as different accounting standards and local regulations that force companies to report figure in certain manners, as well as nature and prevailing weather conditions, factors extremely important to success of SMEs operating in agricultural industry.

## Quantitative variables

The major aim of research carried out by Edmister in 1972 was to examine whether financial ratios carry any predictive power in explaining future failure of small businesses. Results of his study affirm the belief that financial ratios are valuable predictors of small business defaults and support numerical credit scoring. He looks at researches carried out by Beaver, Altman and Blum and finds some ratios to be good predictors in more than one study, but argues that no group of regressors is common to all. This implies that estimated models can be applied reliably only to cases extremely similar to those of the training sample sets of initial research. It is also important to account for the purpose and scope of each study that resulted in a relevant model and see whether it is applicable to one's case (Edmister, 1972).

There are too many of financial ratios – this is the main problem. Around hundred ratios were found cited in different research paper, with only 50 found to be useful in at least one financial study (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000). Intuitively, important financial ratios come from the group of leverage, liquidity, profitability and activity ratios. However different studies, using different data sets, produce different sets of best performing variables. Richness and dimensionality of data, specific features it incorporates, like certain industry or sector of economy, as well as noise within it, eventually constitute the set of optimal financial ratios.

While relationship between financial ratios and default exists, it is not obvious what is the exact shape of it, what the most powerful ratios are and how does the correlation between the explanatory variables affect the respective coefficients. Paper of Falkenstein et al (2000) discusses the criteria that a suitable financial ratio should satisfy. Good variable is the one that has the most conditionally monotonic relationship with independent variable, i.e. either increasing or decreasing over the whole observation range without changes in the slope of the relationship over the range. When choosing the right predictor one needs to look for the one that will produce a steeper relationship with probability of default. Conditionality refers to the independence of relationship of size, industry, geography, etc. An example of such variable is liquidity which is negative for small firms and is positive for large corporate; such instability of relationship will not cope well with the out-of-sample prediction (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000). Sales growth variables, on another hand, are good examples of non-monotonicity: lower sales imply weaker prospects and, therefore, higher PD. On the other hand, high sales imply rapid expansion and increased demand for financing, which might be difficult to accommodate, as future developments aren't always as predictable and may lead to higher PD. Such growth for SMEs is to be financed by external borrowing costly, and not out of profits or retained earnings, thus, escalating the burden of debt and associated risks (Hayden, Are Credit Scoring Models Sensitive With Respect to Default Definitions? Evidence from the Austrian Market, 2003).

In their paper Falkenstein et al. (2000) present a good analysis of possible issues that can arise when dealing with financial ratios. As they note, it is often the case that a single financial ratio is related to a number of risk sources, like retained earnings/assets. Inclusion of many financial ratios formed from similar sources of risk can spark excessive correlation among the explanatory variables. Analyst should look separately at numerator and denominator as possible explanations of why this may occur. If this is the case one needs to turn to alternative measure of similar risk. Plus, some of the variables have to be excluded from the analysis due to the data unavailability or difficulties of interpreting them. Authors consider the example of Net Income/Equity ratio. Here both composites of the ratio proved empirically to be able to take negative values. In such a case losses would imply lower PD, when equity is negative, which obviously contradicts logical reasoning (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000).

One also has to be cautious of the fact that same ratios can be of different importance and predictive power when considered for SMEs as compared to large corporate. Good examples are leverage and liquidity ratios. While being one of the most important predictors for large corporates, leverage ratio ranks among one of the least important form smaller firms. Liquidity is an important factor in many credit decisions since it is a contemporaneous measure of default: if a firm is in default, its current ratio must be very low. While short-term to long-term debt appears of little use in forecasting PD for SMEs, cash to assets proves to be the most important single variable for small firms as compared to larger firms (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000).

Lenders are often more interested with where the debtor is heading rather than what his past condition was. Analyzing firm over time, however, allows the expert to at least understand whether entity's risk has increased or fallen. Empirical studies show that trends in certain financial ratios are important factors of their own, like change in profits and liabilities. Ratio level by itself is ambiguous and incomplete information, but deterioration in approved borrower's financial health, reflected in falling earnings, reduced liquidity or equity, is unambiguously bad. Despite their importance and the fact that virtually every firm that fails shows declining trends, trends are usually dominated by levels. Several studies show that, on average, financials ratio levels perform better than the corresponding trends in explaining PD (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000).

Interestingly, as research of Vallini et al. (2008) highlights, variations in ratios can be due to potential different attitudes towards risk, owners' versus creditors' demands issues, differences in marketing strategies, differences in salaries and service contract charges from supplies, implying that unfavorable level of ratio may not necessarily signal a bad counterparty, but certain internal features with temporal basis directed towards certain goals (Vallini, Ciampi, Gordini, & Benvenuti, 2008). However, it is important to argue that be such decisions internal and temporary, they still expose company to a certain amount of risk reflected in the level of corresponding ratios, neither limiting nor excluding possibilities for such decisions to result in a default or financial distress of the company. The latter argument supports the value of financial indicators as objective (in this light) indicators of true distress vulnerability.

As Falkenstein (2000) notes, financial information of a company ages quickly – it appears to weaken after only one year. It is a good implication when gathering information for the estimation as it is often costly to obtain more annual statements. It is, therefore, important to obtain more recent statements and not get carried away with whatever happened five years ago.

## Selection and transformation of variables

Most analysts construct models based on model selection heuristics. This is true, in spite of development of model that take into account the model uncertainty. Falkenstein et al. (2000) outlines two main methods for selecting appropriate variables: forward selection (SFS) and backward elimination (SBS). The former starts with multivariate specification that includes most powerful variables based on their univariate statistical significance and adds the ones with lower significance until additional variables bring no additional significance to the model. The latter, on the other hand, start with specification inclusive of all explanatory variables and then proceeds with exclusion of all the insignificant ones. Forward selection has biased estimates, as assumptions of the t-tests are violated, but is still used as a common rule-of thumb. Falkenstein (2000) notes that former is generally preferred over latter due to intensive number of potential variables attributable to backward elimination process. A useful start is to analyze the univariate power of variables for determining their further inclusion into the multivariate model. Once important variables are included into the model many different sets of their coefficients produce an output similar to the one of optimal model (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000).

Hayden et al. (2009) propose Bayesian model averaging (BMA) as a coherent way to form a weighted average of a class of possible models, using weights corresponding to the relative likelihood of every model, given the data set. There are a large number of regressors that can be considered when estimating a model. If the number is k, then there are $2^{k}$ possible prediction models stemming from these regressors. While model selection procedures are algorithms aimed at selecting one of these $2^{k}$ models, model averaging procedures form weighted average of these models. In case of SFS, at each step of adding one more explanatory variable to the model specification makes the procedure rely on the p-values that are conditional on previous steps taken in the selection process, which are adjusted improperly. Moreover, it was found that procedures tend to be susceptible to correlations between the possible regressors. Bayesian model averaging, on another hand, allows accounting for the model uncertainty by forming a weighted average of possible models, where each models weight is its posterior probability (Hayden, Stomper, & Westerkamp, Selection vs. Averaging of Logistic Credit Risk Models, 2009). Through the bootstrap analysis authors compare BMA with two step-wise selection models, SFS and SBS, to find BMA to outperform the two latter in terms of cardinal performance measures (Brier and logarithmic scores), while underperforming in terms of accuracy test. When models are to be used for generating credit scores, all three models were found to be similarly powerful. However, if the model is to be used to produce probability of default estimates, BMA is seen preferential. Authors go further to analyze possible causes of superior performance of BMA over SFS and SBS. They argue and conclude that if stepwise model selection is to be used, candidate regressors should be mapped into smoothed log-odds of default, as such transformation is found to improve the performance of stepwise model selection procedure with regard to BMA (Hayden, Stomper, & Westerkamp, Selection vs. Averaging of Logistic Credit Risk Models, 2009).

Adding more explanatory variables to the model increases the power of the model as measured by r-squared, while also increasing the variance of coefficients, in which case confidence increases at expense of models validity. The issue is known as overfitting of data. High degree of correlation between independent variables will likely result in poor out-of-sample performance of the model and erode interpretability of true causes of default. As Falkenstein et al. (2000) suggest, after a certain point, additional information brings in confusion in the form of worse predictability. Yet, complete independence between input variables is not necessary: multicollinearity is deemed acceptable as long as it not greater than 0.2 (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000).

Since many ratios are nonlinear in their relationship with probability of default, transformation of variables is essential for establishing an optimal model. One common method is to standardize the data by removing the mean and dividing by standard deviation. However, it usually leaves asymmetric and fat-tailed regressors, let alone the imposition of a strict functional dependency between PD and a variable. Methods found useful in analyzing small business default are:

- classification of a ratio into quartiles
- trend analysis
- combinatorial analysis of trend and level of a ratio
- calculation of three-year average
- division of a ration by its respective industry average (Edmister, 1972)

## Dataset issues

When considering data to be used for estimating a credit risk assessment model based on information from financial statements of companies in the sample, it is important to note how many firms there are in the sample with consecutive financial statements, as it is the multiple statements that would allow us to pick out the trends in the key financial ratios that help predict default. At the same time, as we noted earlier, financial information of a company ages quickly – it appears to weaken after just one year. It is, therefore, important to obtain more recent statements and not get carried away with whatever happened five years ago. Plus, it is a good implication when gathering information for the estimation as it is often costly to obtain more annual statements.

Financial statement quality is the crucial part if the estimation is based on data compiled from companies' financial statements. An important aspect of data quality brought to the attention by European Federation of Accountants (2005) is the fraud and "cooking" of financial statements by the SMEs. Audit is the highest level of quality, but also being the costliest. The latter is important especially for the scale of companies we are considering, SMEs. In such case, such costs would often exceed the benefits derived from such practice. Also, audit information is useful, if less than what we would like. Research shows that those firms who changed auditors had a 50% greater probability of default as compared to those that didn't (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000). It turns out that audit is highly correlated with the size for the smaller companies and most of it explanatory power, thus, contained in the size variable.

Also, when choosing which type of model to estimate it is useful to consider the data at hand. Panel data sets are said to offer several advantages over traditional cross-section or time-series data, which should be exploited whenever possible. To mention a few, such data allows alleviating the problem of multicollinearity among regressors, as they are less correlated when they vary in multiple dimensions. The problem with panel data, however, may arise, when one has unbalanced or incomplete panel data (Hayden, Are Credit Scoring Models Sensitive With Respect to Default Definitions? Evidence from the Austrian Market, 2003). When data is unbalanced, the model tends to focus on the prevalent class and ignore the rare events. As a remedy one can use a strengthening process of learning with respect to the rare events. Menardi (2009) proposes strategy to balance the distribution of classes through the use of Random Over-Sampling Examples (ROSE). This strategy allows balancing the distribution of classes by generating new synthetic data from the two conditioned distributions assumed. As a result, an augmented sample size helps in estimating the model, as the classifier will address the initially rare class with same attention as initially prevalent (Menardi, 2009). This issue corresponds to the one highlighted by Falkenstein (2000) of scarcity of data with rich default events. ROSE includes most of existing re-sampling methods as a special case, and gives advantage of both reducing the risk of overfitting with bias towards prevalent class and increasing the classifier's ability to generalize. But doesn't it produce an artificial set of additional data biased towards the choice of distribution one assumes when generating synthetic examples?

Working paper of Financial Services Authority stresses the importance of "Missing defaults" issue in data sets, which can take the form of unrecorded defaults (which could be a result of weaker definition of default), not yet recorded defaults, omitted defaults as a result of deliberate policy action, data inefficiency if collected externally. The effect of missing defaults is to reduce PD and therefore capital requirements (Financial Services Authority, 2007).

Problem related to the same issue was encountered by Hayden in her research on Austrian SME testing for the impact of different definitions of PD on model specification. She found ratio of defaults to be volatile and unstable for different years. This was so as not all banks in the study were able to provide default data for the selected years with other banks or weren't able to provide for the whole period selected of 1987-1999. Also while some banks were reluctant to provide information on good borrowers, but not so on bad ones, other banks did not record their default for certain periods at all. Hayden also notes that when compiling financial data from different sources it is extremely important to guarantee that accounting schemes of involved banks are made comparable (Hayden, Are Credit Scoring Models Sensitive With Respect to Default Definitions? Evidence from the Austrian Market, 2003).

Importantly if a model is estimated using only observations accepted by the provider of data sample, it will contain the effects of previously used selection methods that are to be reviewed and potentially replaced. As a result, authors adopt approach of building scoring models on accepted and rejected applicants separately, estimate the performance on rejected sub-sample and, by applying the relevant cut-off, build a new model. Also, since the cost of accepting a bad applicant (Type I error) is costlier to a firm than foregoing a good one (Type II error), it is important to see the accuracy of each model separately for good and bad applicants (Bensic, Sarlija, & Zekic-Susac, 2005).

Falkenstein et al. (2000) point towards the data bias that is usual when it comes to analysis on smaller firms. They argue that many defaults are added manually to the databases which are used for research and it is common that larger firms' defaults are more notable due to magnitude. Hence, they state that using manually maintained databases on defaults, it is mostly the case that size and default are positively correlated: larger the size, higher is the PD. The opposite relationship is true for smaller firms. Supporting the argument, Vallini finds that firm's greater size increases model's accuracy as small firms will naturally have smaller figure in their statements with even small changes potentially resulting in serious posterior effects. Moreover, in terms of what they can reveal about a company, certain ratios are completely uninformative below certain levels (Vallini, Ciampi, Gordini, & Benvenuti, 2008).

As Falkenstein et al. (2000) suggest models can also have a problem of power degradation over different sample sets. This could either be due to: (1) differences in default rate frequency among sample sets, or (2) different sample sets having different degrees of noise in explanatory variables. Also, some of the loss of power could stem from the fact, explained earlier, that default rates are measured better for rated firms compared to unrated and public firms compared to private, i.e. data set bias. The above issue states importance of drawing inferences on predictive power of one model over another only in the case of comparing the two over identical sets of data (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000).

## Impact of differential treatment of SMEs on capital requirements for banks

Throughout the study we pointed to the financing gap suffered by the SMEs, a sector that is a major contributor to growth in many countries and grows in importance as economies evolve and get more developed. Combining that with the fact that till today banks are the major source of smaller firms' financing, it is vital to understand impact and consequences that banks are faced with, when providing credit to the SMEs. Importance of special attention devoted to SME credit scoring is supported by the new regulation under Basel II, whereby SMEs loans will receive a different treatment than corporate loans and will require lower capital requirements. The main reason for that is the argument that SME credit risk is less systemic and is more vulnerable to idiosyncratic shocks, i.e. risk factors specific to the firm, thus implying less of contagion effect between SMEs as compared with corporate borrowers.

SMEs under standardized approach for credit risk under Basel II can be subject to the following treatment:

*"69. Claims that qualify under the criteria listed in paragraph 70 may be considered as retail claims for regulatory capital purposes and included in a regulatory retail portfolio. Exposures included in such a portfolio may be risk-weighted at 75%, except as provided in paragraph 75 for past due loans."* (Basel Committee on Banking Supervision, 2006).

The above means that given that SME exposure is not past due and satisfies the definition of retail exposure, it can have a risk weight of 75% instead of 100% that would have been applied otherwise since SME would have been regarded as an unrated corporate.

Under internal ratings based (IRB) approach, treatment of SMEs is subject to further adjustment:

*"Under the IRB approach for corporate credits, banks will be permitted to separately distinguish exposures to SME borrowers (defined as corporate exposures where the reported sales for the consolidated group of which the firm is a part is less than €50 million) from those to large firms. A firm-size adjustment (i.e. 0.04 x (1 – (S – 5) / 45)) is made to the corporate risk weight formula for exposures to SME borrowers. S is expressed as total annual sales in millions of Euros with values of S falling in the range of equal to or less than €50 million or greater than or equal to €5 million. Reported sales of less than €5 million will be treated as if they were equivalent to €5 million for the purposes of the firm-size adjustment for SME borrowers.*

*Correlation (R) = 0.12 × (1 – EXP(-50 × PD)) / (1 – EXP(-50)) + 0.24 × [1 – (1 – EXP(-50 × PD)) / (1 – EXP(-50))] – 0.04 × (1 – (S–5) / 45)"* (Basel Committee on Banking Supervision, 2006).

In the above formulae S represents annual sales and lies within the interval {5; 50} and thus has a downward effect on correlation, which in turn implies a decreasing effect on Capital Requirement and Risk-weighted Asset (RWA).

This amendment in regulations to treat SME differently was a result of extensive criticism of the Basel Accord which was claimed to be over-reliant on external credit ratings, what results in cyclically lagging rather than leading and forward-looking capital requirements (Jacobson, Linde, & Roszbach, 2005). Hilscher and Wilson in their paper of "Credit Rating and Credit Risk" find that superior performance of a simple model based on publicly available financial information at predicting default is not due to infrequent migration of ratings, nor due to the ratings' use of broad and discrete rating. They find that there is a significant overlap of default probability distributions across investment grades: many firms characterized by similar default probabilities see their ratings quite different, suggesting that variation in rating explains very little variation in raw PD (Hilscher & Wilson, 2010).

Altman and Sabato conducted a study on over 2,000 SMEs of USA to build a one-year default probability prediction model (Altman & Sabato, 2007). They conclude that by segregating their loan portfolios between corporate and retail exposure, banks are able to benefit from lower capital requirements, which would have a downward pressure effect on cost of financing for SMEs (Altman & Sabato, 2007).

Jacobson et al (2005) carried out research to investigate if differential treatment of loans to SMEs and large corporate was justified by the loss distribution of data in the frame of their sample size. Though the application of non-parametric Monte Carlo simulation method in estimation of portfolio loss distributions, they find, firstly, that, although both SME and corporate risk weight mappings capture the broad movements in portfolio of credit risk, cases are present when equal credit risk assets are associated with different regulatory capital. Secondly, that the SME risk weight function proves to have highest power at capturing actual credit losses at very small levels of SME. Where the definition converges to the one of Basel II, risk weight function seems to require much larger capital cushion than suggested by the loss distributions. Thirdly, probability of convergence of regulatory capital and economic capital set by bank depend largely on the definition of SME used by the bank and the loan portfolio characteristics, specific to every bank. The main conclusion of the paper is that there is no clear evidence that SME loan portfolios are consistently less risky than the ones of corporate. Changes in SME definition may lead to such relationship. Their results show that using the simple risk weight mapping as suggested by Basel II can lead to substantial inequalities among banks owing to differences in shape of loss distributions between banks and between assets (Jacobson, Linde, & Roszbach, 2005). If a bank doesn't specialize in financing of particular sector, broad SME definition applied to a diverse pool of sectors would result in inherently different firms that fit into the definition. That would shape the SME loan portfolio of a bank, its loss distribution function and eventually capital requirements. Level of regulatory burden for such a bank would differ substantially from that of a bank that specializes in financing of a particular sector, having distinct loss distribution.

# CHAPTER 4

## Research results and conclusions

Given the importance of the SME sector as a major contributor to economic growth and employment across the world, it is essential to have sound support infrastructure in place. Smaller companies can generate increased enterprise value and benefit substantially from eased access to capital. For that governments need to understand the unique features of smaller companies and problems they face, find will power to enforce reforms aimed at support of these business entities, including but not limited to the likes of privileged taxation and loan interest rates, award of contracts in certain areas exclusively to SME sector, access to informational data bases, support in formation of networks and clusters within SME sector as well as with MNEs, and others.

Unique nature of SMEs advocates different approach towards measurement of credit risk of these business entities. This fact is reflected in proposed differential treatment of the sector under the Basel bank regulations, where numerous studies showed the beneficial impact of such practice on capital requirements for banks – main lenders to the sector in today's economy. In diversifying sources of credit to smaller companies, it is vital that along with bank lending, practices of trade credit become more common in doing business with SMEs. This in turn requires sound understanding and successful development of credit risk management in companies closely engaged in business relationships with the sector. This study sheds light upon some of the most important points that require attention in development of credit risk measurement techniques for SMEs starting from choice of model, philosophy and regressors, as well as definition of default and analysis of default dataset.

Major deterrent to the adoption of credit risk measurement models is seen to be the complexity of statistical systems. Managers are reluctant to adopt such models if they find it hard to or don't fully understand the models. Simplicity is therefore an important pre-requisite of successful adoption in an industry.

The best default evaluation model in case of SMEs would, probably, include large portion of qualitative analysis with access to in-depth knowledge of the firm's management and competitive advantages at firm's disposal. Such information is difficult to obtain, however, and more so if time is limited. While most defaults are preceded by observations of deterioration in financial health of the company, it is also frequent that a small firm, as any other, falls victim to some external shock. Even if the firm's insolvency is triggered by an external event, firm's data will show potential and pre-existing areas of vulnerability allowing certain external events to prompt fatal consequences (Vallini, Ciampi, Gordini, & Benvenuti, 2008).

Studies of Beaver (1967), Altman (1968), Edmister (1972) stressed the importance of financial data in predicting default, variables selection process and advocated the use of statistical analysis (Falkenstein, Boral, & Carty, RiskCalc(TM) For Private Companies: Moody's Default Model, 2000). Since then many models were developed of increasingly different functional forms: from discriminant analysis and Z-score to Case-Based Reasoning (Lin, Wang, Wu, & Chuang, 2008) and Random Survival Forests (Fantazzini & Figini, Random Survival Forests Models for SME Credit Risk Measurement, 2009). Many scholars carried out comparative studies on predictive power of different models and, while some papers found simpler models better, other studies prompted support to more sophisticated ones.

Fantazzini and Figini have attempted to answer the question as to why the simple logit model performs better than a more complex one as the likes of RSF. Their study confirms the previous findings that simple models typically yield performance almost as good as more sophisticated methods, to the extent, that the difference in the predictive power can be overshadowed by other sources of uncertainty, generally unconsidered in a classical classification paradigm (Fantazzini & Figini, Random Survival Forests Models for SME Credit Risk Measurement, 2009). The bottom-line, however, is that the true comparative power of one model over another can be judged only once tested on same sample test that represents the default and non-default class. The latter is difficult if not impossible as SME definitions vary across countries and industries. As a result, models can be judged for better predictive power only over a specific region and specific industry. Importantly, since the cost of accepting a bad applicant (Type I error) is higher than foregoing a good one (Type II error), it is important to see how an estimated model performs with respect to the two statistics.

Besides general characteristics of an optimal credit model like efficient, robust, valid, reliable, intuitive, transparent, an SME's model should possess the following features: time and cost efficient; make use of limited financial data available for SMEs; be able to work with only one year of financial data; broad applicability (Rikkers & Thiebbueault, 2007). Accounting-based statistical credit scoring methods are the most common for small and private firms. Use of statistical credit scoring model in collection process advocates the emphasis placed on inherent risk characteristic of the borrower as opposed to aging items on its account. Why is statistical model preferential to judgmental then? Reason is that latter informs on quality of the risk separating lowest risk accounts from highest ones, while statistical model quantifies the risk by informing you on the probability of default and, therefore, associated expected loss, i.e. value of the risk (Driving Internal Collection Results With Statistical-based Credit Scoring, 2010).

Credit scoring today is becoming a more and more powerful tool in automation of credit risk analysis and collection of the company's accounts receivables portfolio, with largest assets on most companies' BS. One of the main reasons behind it is rapid technological advancement. Purpose is not to restrict the credit but to optimize the credit risk across the entire accounts receivables or loan portfolio. The main aim is to maximize profits by managing the risk in the portfolio. Credit scoring can help companies to boost sales through increased credit lines, expanding sales to marginal accounts or by better identifying potential customers. It may result in bad debt losses, but as long as the scoring model is used efficiently, higher profits from increased sales volumes will overcompensate for losses due to bad debts (Michalski, Portfolio Management Approach in Trade Credit Decision Making, 2007).

It is important to identify and choose the relevant philosophy when constructing a credit risk assessment model. This would also have impact onto which explanatory variables to be used. Although a 5-year period span might seem to be more useful, since very few firms default in first and second years of existence as per mortality curve, accounting for the fact that smaller firms are generally more vulnerable and sensitive to both, internal and external shocks, than their larger counterparts in the short run, it is optimal to adapt a PIT approach when measuring credit risk of SMEs. This would allow the score on any particular company to be more up-to-date with information entering the market that pertains either to this company directly or the industry it operates in. PIT approach, by providing early signals, would allow the lender to take precautionary measures faster in order to secure collection of outstanding liability of a debtor and reduce the exposure by placing a lien on the goods under custody, in case of trade credit. Past research advocates this view. Most papers revolve around probability of default estimation for 1 year horizon. Within this time frame certain important events can be observed:

- raise of new capital
- loss mitigation action
- new information on borrower
- default data publishing
- issue of financial statements
- renewal of credit facilities (Hayden, Are Credit Scoring Models Sensitive With Respect to Default Definitions? Evidence from the Austrian Market, 2003)

Adopting definition of default where event of default is considered as point of official filing or declaration of bankruptcy presents perspective of worthless or destined to fail credit risk assessment model, when lender estimates model based on data with default observations occurring far past the point of initial deterioration of financial health of the company, thus running the risk of developing a model that is able to forecast defaulter only when it is actually too late to take any action to reduce exposure and minimize losses – a fact that contradicts the main purpose of any credit assessment model. Given the proposed horizon philosophy from previous section, an optimal definition of default for SMEs would be with default defined as event when debtor fails to settle his payment within 90 days. This would allow estimating a model that is able to identify borrowers who start showing payment problems early on and make it possible to initiate corrective action on part of lender without delay.

An important conclusion made by one of the pioneering works, Edmister (1972), that prompted further interest and research in the area is that financial ratios have predictive power of failure for at least five years horizon. He claims the researcher cannot choose the regressors indiscriminantly due to finding of persistent differences in predictive powers among different ratios (Edmister, 1972). Empirical evidence supports the use of both qualitative and quantitative factors in modeling probability of default of a company. Among the important qualitative variables to consider are industry variation, legal form, geographical, political and foreign exchange risks, stage of economic cycle, past credit history and bank relationship. Financial indicators can potentially explain and predict great share of a company's default, but require thorough data processing and transformation in order to avoid multicollinearity, wrong sign effects and overfitting of data to enhance the out-of-sample predictability of the model. This issue is however secondary, given the fact of scarcity and inferior quality of financial statements of SMEs in the first place.

Prior to estimation of the model it is important to analyze the dataset in hand. Key check points for the modeler should include quality of financial statements under consideration, how balanced and censored the sample of default observations is. If financials are unaudited and have a question mark over its reliability, such data is better to be omitted from model estimation. Problem of unbalanced data can be alleviated though the use of data re-sampling techniques, which help remove the bias of prevalent class of observations (Menardi, 2009).

When using the data sourced externally, one has to be cautious of data sampling methods by the data provider as that could result in rationing and omission of important observations. Latter could also occur depending on the size of companies in the sample, as empirical evidence suggests existence of more accurate record of defaults for bigger companies as compared to smaller counterparts.

Each loan that is mispriced or mistakenly granted represents a lost opportunity. Hence, importance of better credit analysis should not be underestimated. Acting as a tool in successfully identifying good borrowers from bad, credit scoring can ration the credit lines of many large companies working with SMEs and divert financing to debtors characterized by sound repayment ability. This boosts their accounts receivables portfolio via the use of value and portfolio-based trade-credit approaches and, hence, increasing their enterprise value. In turn, same reasoning applies to banks providing large corporate with credit lines from their side. It's a self-reinforcing cycle that in generalized form of economy promotes better understanding for banks and companies, providing further trade credit to their debtors, of associated credit risks of the counterparties they deal with. The latter fact is augmented by the possibility of lenders to benefit from it through increased firm value. Positive consequences further emerge in the form of eased access of smaller companies to external financing, enhancing their negotiating power with lending institutions as alternatives to external financing will get more diverse and shift from banking to real sector of economy. The development will prompt increased demand for better credit infrastructure and regulatory framework. The former is likely to occur through establishment of credit rating agencies and risk management consultancy firms, which, in turn, is to have a great impact towards increasing the quality and reliability of financial data of SMEs and to make the services more affordable through increased competition in the service industry of credit assessment. Such effects can only take place once the change is implemented through economies of scale and required reforms in banking sector and incentive program from government.

As suggestion to improve and extend this research, one can estimate a model in line with the above recommended framework using numerical data and test for its power. Comparison can be drawn between models with similar framework but varying certain criteria, like definition of default or time horizon, where it would lead to inclusion of different and/or additional explanatory variables. This would allow to test the power and usefulness of the arguments applied in this study with respect to the recommended choices of key aspects outlined in the Methodology section.

Empirical tests on power of different models can be carried when estimated on data of SMEs pertaining to specific industry or country as compared to data of generalized pool of SMEs, in attempt to verify the logic that credit scoring should be applied separately on different industries and countries SMEs, thus incorporating industry and country specific characteristics and reducing the noise in data.

Additionally it would be interesting to estimate a model in line with recommended framework that incorporates the effect of SME support and protectionism by government and see the effect latter has on reducing the default rate of SMEs.

Finally, it would be of interest to test for the correlation between the size of SMEs and prediction power of qualitative variables group as compared to the quantitative.

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