Credit risk assessment: Enterprise-credit frameworks

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Abstract

This paper provides succinct frameworks for credit-risk assessment in the enterprise-credit domain (SMEs and larger businesses), that can guide lenders when choosing appropriate data and tools. Traditionally, lenders relied upon judgmental assessments of the five Cs (capacity, capital, character, collateral, and conditions), but modern technology has allowed them to amass and capitalise on data. Besides judgment, lenders can also apply scoring, reduced-form, and structural models—with the choice being dependent upon the size and nature of the firms being assessed. For the largest companies with traded securities, reduced-form and structural models can be used to interpret their prices and price movements. In contrast, credit scoring is used mostly in data-rich small-business credit environments, but can add value elsewhere. Entrepreneurs' personal data play a major role for the smallest firms, but enterprise-specific data (transactional, trade-creditor, financial-statement) take over for larger companies. Even where numbers are small, it is still possible to develop scorecards to predict agency and internal rating grades. Financial-statement data is a key component, and this paper presents results showing that underwriters' expertise can be harnessed to develop financial-ratio scoring models whose results approximate those developed using empirical data.

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1 Introduction

Credit scoring is used primarily for retail credit, where the rich availability of data makes it the 'gold standard' of credit-risk assessment. For many years, its use was limited to account-level application-scoring for consumer credit, largely because this was where the quickest wins could be achieved.[1] In recent years though, larger lenders have applied the same technology and experience to the small-business segment (which in the USA came at the expense of smaller lenders). According to Thomas (2000), this evolved as lenders realised there was little difference, *ceteris paribus*, between lending to an individual and a one-man business—because their fortunes are so closely intertwined.[2]

Credit scoring may be ill-suited for larger firms though, especially if more appropriate techniques are available. Commentators such as Allen et al. (2003), who are more familiar with the wholesale market, see credit scoring as second choice because of its 'portfolio approach', referring to its reliance upon a historical review of similar cases, as opposed to factors specific to each case. Even so, it has been gaining increasing acceptance for middle-market companies where the amount of data has been growing, as has lenders' ability to assess it, and use it for pricing, limit setting, or ongoing risk management. This demand comes not only from lenders, but also their shareholders, trade creditors, regulators, and others, and is increasing even further with the Basel II Accord. This trend cannot carry on forever though, as there are hurdles (data availability, model validation, consistency across organisations) that prevent larger wholesale loans from being managed as portfolios (Basel Models Task Force report, 1999, cited in Ong 2002).

This paper takes a brief look at some of the different types of data and models that can be used. It is primarily a literature review, but is unique in that it covers both retail and wholesale lending in a few pages, presenting concepts in a manner that should ease interpretation. Most has been extracted from my book, 'The Credit Scoring Toolkit'. Also presented is a small-business data-requirements matrix, a framework being presented for the first time, that can aid lenders to determine what data is required for small and middle-market companies at different stages during the credit risk management cycle.

2 Credit-risk assessment 101

Risk assessment is easiest in instances where past experience can be combined with data. The extent to which this is possible depends upon the type of risk. Olsson (2002) presents what he calls an 'uncertainty matrix', an adaptation of which is provided in **Figure 1**. According to this, the greater the certainty of the possible outcomes and their probabilities, the easier the risk is to measure. Thus, it is relatively simple to assess market, liquidity, and credit risk, but much more difficult to assess operational, country, reputation, and systemic risks. The primary constraints are data availability and the curse of rare events.

Risk measurement relies upon having data, and tools to turn it into information. The types of data used can be classified according to: (i) source—internal systems, customer supplied, or external agencies; (ii) frame—time series (vertical) versus multivariate snapshot (horizontal); (iii) judgment—objective (empirically derived) or subjective (human opinion); (iv) indicators—leading or lagging; and (v) view—backward (historical data) or forward (judgment/market prices). The ideal is to have forward-looking indicators, but that is infeasible in volume-driven environments. There are no market

[1] According to Makuch (1998:3), 'It is estimated that as much of 80 per cent of the 'measurable and controllable' risk is decided upon at the time of underwriting'.

[2] The first generic attempts were provided by Fair Isaac, who launched a Small Business Scoring Service (SBSS) in 1993 (Asch 2000), a trade credit service called CreditFYI.com in 1998, and a loan credit service called LoanWise.com in 1999 (Allen et al. 2003:13).

prices for individual loans, and subjective assessments are inefficient, and expensive. Even so, credit-scoring models have proven extremely robust, if only because of the inferences that are possible, given sufficient and stable historical data. In need, lenders can adjust strategies to accommodate their assessment of the future at portfolio level.

The first tool used for providing structure to credit-risk assessment, was the concept of the 5 'C's, a framework that could be almost as old as credit itself.

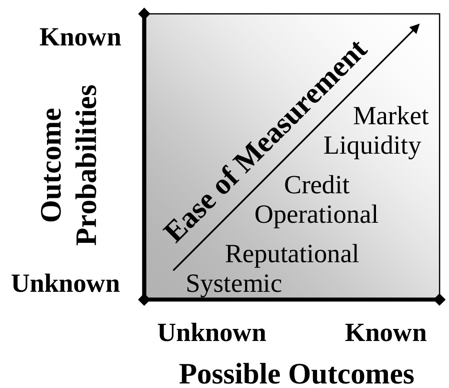

Figure 1. Ease of Measurement

Capacity—Ability to repay liabilities out of income;

Capital—Financial resources available to meet commitments should income not materialise.

Conditions—How the current environment may impact upon the enterprise, whether via competition, economic, industry, or other factors.

Character—The quality of management: Who are they? What experience do they have? Are they well suited to lead the company?

Collateral—Security provided, including the pledge of assets, guarantees from third parties, or other risk mitigation.

This framework still dominates where information is obtained directly from the client in relationship lending. The task now is to determine how this relates to modern environments, where further structure has to be imposed upon the risk assessment. The goal is to minimise subjectivity, which requires data and/or experience.

3 Risk Assessment Revolutions

Credit-risk assessment has undergone its own industrial and technological revolutions over the past two hundred years. Its industrial revolution started with the broader industrial revolution, and evolution of consumer societies. It resulted from the imposition of structure upon the process, which was required where lenders' employees made the decisions. Means had to be found of conveying hard-earned experience from one generation to the next—including the development of policy and override frameworks, concepts like the five 'C's, and tools like ratio analysis.

Policy: Rules used to limit the decision, when certain conditions hold true. These are usually based upon past experience, especially where higher than normal losses are associated with those conditions.

Overrides: Decisions can be overturned by other (usually higher) authorities, whether people or policies. Judgmental overrides of policy rules should only be done, if they can be motivated by information that is not recognised by the existing framework.

In contrast, the technological revolution is more recent, and has been reliant upon computers to speed and streamline the data collection and analysis process. It provided an entirely new dimension to the range of options available. As illustrated in **Figure 2**, pure judgment and policy have given way to the use of different types of models. The choice depends upon the desired level of structure, and the amount of available data:

Pure Judgment: Low on structure, low on data. Relies upon subjective assessments, with no model or template.

Expert System: Little data exists, but xunderwriters have sufficient experience to develop a set of rules or model, that can be used to either drive or guide decisions. They are seldom reliable enough to be the sole decision driver though, and there will usually be a judgmental overlay.

Hybrid Models: Data availability varies. A combination of model types is used, depending upon what can be constructed for different aspects of the risk assessment. Outputs from different statistical, and possibly expert, models are integrated into a single model.

Statistical Models: High on structure, high on data. While predictions are more reliable, they have the disadvantage of a data addiction—and only the best and most highly structured data will do.

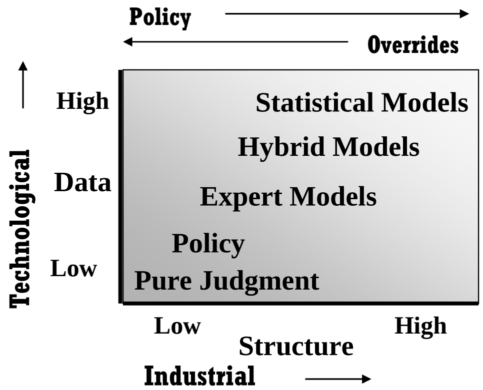

Figure 2. Risk Assessment Revolutions

An overview of the mix between pure judgment and statistical models for different types of lending is provided in **Figure 3**. The matrix has transaction volumes and potential profit as the x- and y-axes respectively. The upper-left quadrant contains wholesale credit sectors where little data or experience exists, and the potential profits are high—especially true for large and/or complex loans, such as sovereign, corporate, and project-finance lending. These areas suffer most from the highly unstructured nature of what little data is available.

In contrast, the lower-right quadrant contains retail credit—especially consumer and small business lending—where statistical models provide the main voice. These have limitations though, and are only the better choice where: (i) the environment is relatively stable; (ii) the data is highly structured; (iii) the loss associated with individual transactions is relatively low; (iv) lower costs are perceived to provide a significant competitive advantage; and (v) there are sufficient volumes and potential profits to justify the investment.

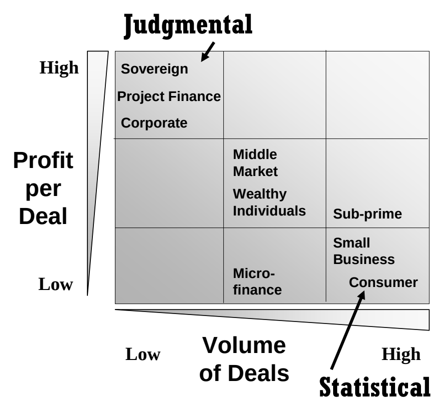

Figure 3. Volumes and Profits

According to Chorafas (1990), the Pareto principle also applies to credit. A very small proportion of customers often provides the greatest proportion of profits! Thus, service offerings should be stratified, according potential profitability: 'Emphasis must necessarily be placed on the most lucrative parts of the market—which is often more demanding, more risk, and also requires a steady vigilance in product development, as there is no copyright in the finance business'.

The treatment of the different types of lending is not cast in stone, and over time, the thresholds have been shifting. Risk assessment skills have become fewer and dearer, while data has become broader, deeper, and cheaper. As lenders become more comfortable with credit scoring, it is increasingly being used to assess individuals and companies where ever larger values are involved.

4 Data and Tools

Risk assessments can be done using a number of different data sources, and tools other than scoring and judgment. The available data sources are:

Payment history: Information on borrowers' payment patterns, which is a loose surrogate for character/management.

Principal assessments: A look at the entrepreneur(s) behind the business, including their credit histories.

Financial statements: A review of obligors' financial positions, as presented in recent balance sheets and income statements.

Environmental inputs: Review of industry and regional factors, whether using economic data and forecasts, or historical aggregates based on internal/bureau data.

Market value of traded securities: The level, volatility, and buy/sell spreads of market prices provide forward-looking information, which is a summary of market participants' views on obligors' credit risk (the gold standard for corporate credit). Both bond and equity prices may be used.

Human input: Relationship managers' and underwriters' eyes and ears are still a primary source of information. The goal is to ensure that their observations are as objective as possible, but in many instances, subjective inputs are required.

This list is not exhaustive; other sources, such as application forms and credit evaluations, could also be included. Each provides information on one or more of the five 'C's (see **Table 1**). The most far reaching are judgmental assessments and the value of traded securities (both forward-looking), but judgmental assessments are expensive and slow to react, while securities' prices tend to overreact.

Table 1. Data versus the 5 Cs

Data Source	Capacity	Capital	Conditions	Character	Collateral
Human input	✓	✓	✓	✓	✓
Traded securities prices	✓	✓	✓	✓	✓
Financial statements	✓	✓			✓
Environmental inputs			✓		
Principal assessments				✓	✓
Payment history				✓	

Exactly what data is used also depends upon the amount (to be) borrowed, and the size of the obligor being assessed. The 'loan amount' drives what information is requested, while 'firm size' affects what is readily available and relevant. If both are small, the time and effort spent on the assessment will be less. **Table 2** provides an indication of the large number of smaller companies (excludes sole proprietors) in the United States, and the pattern is similar elsewhere. Indeed, the bulk of economic growth is driven by SME activities. The 'class' definitions vary from country to country, but the general pattern of what information is available and used for risk assessments will be similar (see **Table 3**):

Table 2. USA Companies by Assets
1996 IRS data[3]

Class	Range	Number
Small	<$100K	2,500,000
Small, Middle	$100K-$1M	1,500,000
Middle	$1M-$100M	300,000
Large	>$100M	16,000

3 Falkenstein et al. (2000:11).

Very Large— Share and bond prices can be used for publicly-listed companies and those with traded-debt.

Large—Judgmental assessments dominate for larger companies with significant debt. This applies especially to rating grades provided by credit rating agencies, but also to internal grades. Payment histories and personal assessments are not considered relevant.

Middle—Caught in a range where there is neither market data, nor sufficient exposure to justify full fundamental analysis. Analysis becomes backward-looking, focussing upon what has happened to obligors in similar circumstances in the past. The primary data used is financial statements provided by the borrowers, along with industry assessments. Payment histories and personal assessments may feature.

Small—Below a certain level, financial statements may be either unavailable or unreliable (out of date, poor accounting/auditing, or just plain over-optimism). Focus then shifts towards obligors' payment histories (via the credit bureau) and data on recent revenue inflows that can be confirmed from bank statements.

Very Small—Finally, at some point, it becomes difficult or impossible to divorce the individual and the enterprise, especially for sole proprietorships. Lending will be based on, or heavily influenced by, assessments of the borrowers in their personal capacities.

Table 3. Company Size versus Data

Company Size	Market prices	Judgmental inputs	Environment Inputs	Financial statements	Payment history	Principal assessment
Very Large	✓	✓	✓	✓		
Large		✓	✓	✓		
Middle		✓	✓	✓	✓	
Small				✓	✓	✓
Very Small					✓	✓

Now that the data sources have been considered, the tools used to assess them can be covered. Fernandes (2005) splits corporate credit-risk assessment techniques into three types: (i) structural (e.g. Merton's 1974 option-based model)—models the structure of the default process, using financial statement data (esp. liabilities) and some proxy for asset value and volatility; (ii) reduced-form (e.g. Jarrow and Turnbull's 1995 model)—relies upon the value of publicly-traded debt over time, and assumes that the risk can be determined from price volatility and/or the credit spreads; and (iii) scoring (e.g. Altman's 1968 Z-score model)—describes a target variable as a function of multiple predictors. An obvious omission from this list is judgmental assessments (such as agency and internal rating grades), where credit analysts or committees assess quantitative and qualitative factors, using other tools where possible.

Agency grades are provided by credit rating agencies for a fee. These apply to large firms only, which in 1996 numbered approximately 16,000 in the USA (see **Table 2**). Not all firms are rated though, so the number of rated firms is less.

The appropriate choice is primarily determined by what data is available: (i) structural—financial statement and liquid traded-equity prices; (ii) reduced-form—liquid traded-debt prices only; (iii) scoring—financial statement, trade creditor, and other company data; and (iv) judgmental—where data is thin, highly unstructured, or can significantly enhance the results of other models. Other names are used for these model types, and there are more yet. Falkenstein et al. (2000) mention: agency ratings (judgmental), public-firm (structural), private-firm (scoring), hazard (reduced-form), business reports (scoring), and consumer bureau for SME's (scoring). Two further types complement the other models: (i) exposure models, that predict loss severity should default occur (EAD and LGD), based mostly on collateral type, security, and industry;

and (ii) portfolio models, that recognise within-portfolio correlations and provide overall worst-case loss scenarios at different confidence intervals.

Business report scores are provided by the likes of Dun and Bradstreet and Experian to predict bankruptcy, liquidation, or severe delinquency, based on liens, court actions, creditor petitions, company age and size, and trade creditors' data. Bank data can also be incorporated, but access may be limited to banks only.

Once again, a rather imperfect representation of the relationship between the various model types and data sources is provided in **Table 4**. Its primary shortcoming is that it does not recognise the inroads the lenders are making in integrating model types. In particular, agency ratings and private-firm models are increasingly making reference to market prices, either for individual companies or the entire market.[4]

Table 4. Models versus data

Model Type	Judgmental inputs	Financial statements	Traded equity	Traded debt	Environment inputs	Payment history
Agency rating	✓	✓			✓	
Public-firm		✓	✓			
Private-firm		✓			✓	
Hazard				✓		
Credit bureau						✓

5 Financial statement data

For relationship lending, experienced credit underwriters put heavy reliance upon customers' financial statements (income statement, balance sheet, cash flow), in spite of their faults. Their reliability can be extremely suspect for SMEs, either because of poor attention to detail or the time taken to produce them, and there are costs associated with spreading them into a consistent format. For transactional lending, this information has largely been supplanted by credit bureau data, but lenders ignore it at their peril. Good quality statements[5] can provide a view of obligors' financial health that has a relatively low correlation with—and is more substantial (and longer-term) than—their payment histories. This becomes ever more relevant as the size of the firm increases.

Financial-ratio analysis has long been used for risk assessment of both debt and equity investments. Comparison of defaulted versus non-defaulted firms was first attempted by Fitzpatrick (1932), but Altman's (1968) z-score model was the first to use predictive statistics. Defaults in this domain are very rare though, and it is difficult for individual lenders to amass enough 'bads' to develop a decent model. This is complicated further where lenders lack proper financial-spreading capabilities, especially in retail and quasi-retail environments where it is difficult to cost justify. As a result, financial-ratio scoring remained in the realm of academia for over thirty years, but inroads are now being made.

The two primary modelling approaches are: (i) probability of default (PD)—developed using financial statement and default data collected from many lenders; and (ii) rating grade prediction (RGP)—developed to predict subjective grades provided either by the rating agencies or lenders' own credit underwriters. The first commercially-used generic financial-ratio-scoring PD model was launched by Moody's in 2000, which

[4] According to Dwyer et al. (2004:15), RiskCalc v3.1 from Moody's KMV 'combines forward-looking market information that reflects the general credit cycle and the state of the firm's industry with firm-specific data about private companies'. This is a more sophisticated version than the financial-statement only mode referred to in Section 5.

[5] Financial statements' quality is primarily a function of the resources devoted to creating them, and small businesses are more focussed on business than accounting. In some countries though, taxation or other authorities require regular financial statements, which greatly aids credit risk assessment.

was based upon its Credit Research Database compiled using contributions from many lenders. Today, separate models are available for several geographical regions, but they tend to be better suited for SMEs. [6]

In contrast, Fitch Ratings provides an RGP model, which was developed using the average rating grades provided by all three rating agencies, and is better suited for the wholesale market. Individual lenders can also use this approach to model their internal ratings, using financial and other information. Care must be taken though, as the 'garbage in/garbage out' maxim applies—the results can only ever be as good as the analysts' inputs, whether for the model development or its application. Even so, significant benefits accrue simply from the application of a standard model, even if only provided as one input for into an otherwise judgmental decision.

During 2005 Standard Bank developed an RGP model based solely on expert's blind ratings of 207 SME's financial statements. This was benchmarked against the one- and five- year financial-statement only PD predictions provided by the RiskCalc model for South Africa. The Spearman's rank-order correlations shown in **Table 5** are proof that such expert input can provide reasonable results. While it cannot be shown definitively, the numbers also seem to indicate that: (i) better results are achieved for larger companies where financial statement data is richer; and (ii) the expert's opinions correspond more closely to the longer term projections provided by RiskCalc.

Table 5. Expert Model / RiskCalc correlations

Enterprise Size	Count	1-year	5-year
Small	1,242	72.8%	74.9%
Middle	1,717	86.9%	87.9%
Total	2,959	76.3%	78.2%

6 Small-business data requirements

As indicated in the preceding sections, the data required to assess credit risk varies with the situation. For retail enterprise-lending, the data types can be split into six categories. The first three are those traditionally associated with credit scoring, including: (i) demographics and customer supplied; (i) internal data on current and past performance; and (iii) external data from the credit bureaux. The other three are: (iv) financial statement data, which can be summarised in its own score; (v) collateral, which influences both default probability and severity; and (vi) judgmental inputs, covering aspects that cannot be adequately assessed through objective analysis. These are hardly used for consumer credit, because the costs cannot be justified.

For SME-lending though, there are other issues at play, especially for larger loans where the extra expense is warranted. Financial statements can provide a more substantial view of the enterprise, much of which is not reflected in other data. Collateral may be difficult to realise, but lenders often rely upon the entrepreneurs' personal guarantees that provide extra motivation to come right. And finally, there will always be some point where lenders need to invest that little bit more, and recognise pieces of information that cannot be captured by the system. In some instances this will be through structured questions asked as part of the credit evaluation, and in others through system overrides.

The most complicated aspect of this is integrating the details of both individual and enterprise. This paper is the first in the literature to present the framework shown in **Table 6**, which shows its simplest form. The lender can decide which data is required based upon: (i) whether it is a new or existing customer; (ii) the size of the loan; and (iii)

[6] Gini coefficients for one-year predictions usually range between 45 and 55 per cent (cases scrubbed due to data quality issues excluded), which is comparable to many application scoring models in consumer credit. See Dwyer et al. (2004:26) for USA numbers.

the size of the enterprise.[7] The larger loan, the more expensive the assessment that can be justified. Some of the items are wishful thinking (e.g. financial statements for individuals), but are included here for completeness.

Where there are more enterprises though, the situation is more complicated. Related legal entities are usually groups as 'households', no matter whether these are individuals, juristics, or some combination of the two. The treatment is logical, especially given our cultural predisposition towards mutually-exclusive family units. Is this enough though? Such relationships are often much more complicated. This applies especially to business lending, where obligors can have shared interests in many enterprises. In such instances, the treatment should then shift from households to networks. Rather than just assigning some group number, lenders can instead create linking tables to specify the relationships between the entities, and allow the simultaneous assessment of risk across multiple entities.[8]

Table 6: Data-requirements matrix

	Dem	Int	Ext	Fin	Col	Jud
Business	✓	✓	×	×	×	×
Principal	✓	✓	✓	×	×	×

7 Summary

Credit scoring is usually associated with consumer credit, but was quickly adopted for small business credit where the fortunes of entrepreneur and enterprise are indistinguishable. In recent years, it has been used for the assessment of larger enterprises, but there are limits. This paper discussed several frameworks that can be used to determine which data sources and assessment techniques are appropriate. The starting point was two general frameworks: (i) risk measurability—as a function of the certainties of both outcomes and their probabilities, where credit risk falls towards the higher end of both; (ii) data types—source, frame, judgment, indicators, and view; and (iii) the traditional 5 Cs framework—capacity, capital, conditions, character, and collateral.

In today's environment, the 5 Cs are assessed using transaction histories, financial statements, environmental inputs, market prices, human input, and personal assessments. Which is available or appropriate will vary though, especially by firm size. Transaction histories and personal assessments dominate for smaller enterprises, while analysis of market prices and judgmental review dominate at the upper end. Firm size also influences the types of models that are applied, such as judgmental (rating grades), structural (public-firm), reduced-form (hazard), and scoring (private-firm, business report, consumer bureau). These are complemented by exposure and portfolio models.

Credit has also undergone its own revolutions: (i) an industrial revolution, which resulted from the imposition of structure, that is increased through policy but decreased through overrides; and (ii) a technological revolution that both created and was caused by increased data volumes, that have allowed lenders to shift from use of pure judgment and policy, to statistical, expert, and hybrid models. At the same time, the judgmental/statistical trade-off can be shown as a function of both data volumes and the expected profit per deal—as the latter increases the more likely that judgment will still play a role. Statistical models dominate in high-volume low-value environments, but

7 Related to enterprise size is the number of principals. Beyond a certain point, the enterprise and individual become distinct. According to Nigel Rusby of Experian UK, no more than three principals should be assessed. Similar rules could also be applied to annual turnover, number of employees (if available), or some other measure.

8 If all were done at the same time, this would cause a circular reference. This does not pose a problem for application scoring, which is event triggered. For behavioural scoring though, any assessment would have to use data from the last run.

require highly-structured and stable data, and sufficient profit-potential to justify the investment.

Historically, financial statement data played a significant role in the assessment of both equity and debt investments. In retail credit, it has largely been supplanted by transactional data. Even so, where financial-statement data is good, it can provide a longer-term and more-substantial view of the borrower that cannot be captured by the transactional data of either the business or its principals. Statistical models' targets can take the traditional good/bad form, but bads are even rarer than in the consumer market. As a result, rating grades (internal or agency) are usually targeted instead.

Lenders' challenge is to integrate this information to provide a single assessment. A data requirements matrix for SMEs was presented, which classified the required data as: (i) business and personal; and (ii) customer-demographics, internal systems, external agencies, financial statements, collateral, and judgment. The firm can be treated as an extension of the individual at the lower end, and as a stand-alone entity at the upper end. The problem is the middle ground, especially where several entrepreneurs are involved with interests in different concerns. In such cases, traditional householding approaches are insufficient, and lenders may have to instead consider network modelling. This adds an extra level of complexity though, which may not be warranted.

8 Bibliography

Allen L., DeLong G., and Saunders A. (2003). 'Issues in the Credit Risk Modeling of Retail Markets'. Working Paper No. FIN-03-007. NYU Stern School of Business: New York. <http://ssrn.com/abstract=412520>.

Altman E.I. (1968). 'Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy'. *Journal of Finance* 22, September, 589–610.

Anderson R.A. (2007). *The Credit Scoring Toolkit: Theory and Practice for Retail Credit Risk Management*. Oxford University Press: UK.

Asch L. (2000). 'Credit Scoring: A Tool for More Efficient SME Lending'. *SME Issues* 1(2), November.

Dwyer D.W., Kocagil A.E., and Stein R.M (2004). 'The Moody's KMV EDF RiskCalc v3.1 Model: Next Generation Technology for Predicting Private Firm Risk'. Moody's KMV Company: USA.

Chorafas D.N. (1990). *Risk Management in Financial Institutions*. Butterworth & Co.: London.

Falkenstein E., Boral A., and Carty V. (2000). *RiskCalc™ for Private Companies: Moody's Default Model Rating Methodology*. Moody's Investors Service, Global Credit Research.

Fernandes J. E. (2005). 'Corporate Credit Risk Modelling: Quantitative Rating System and Probability of Default Estimation'. Banco BPI: Lisbon.

Fitzpatrick P.J. (1932). 'A Comparison of Ratios of Successful Industrial Enterprises with those of Failed Firms'. *Certified Public Accountant* 12, 598–605, 656–662, 727–731.

Jarrow R.A. and Turnbull S. (1995). 'Pricing Derivatives on Financial Securities Subject to Credit Risk'. *Journal of Finance* 50(1), 53–86.

Makuch W.M. (2001). 'Scoring Applications'. In: Mays E. (ed.) *Handbook of Credit Scoring*, 3–21. Glenlake Publishing: Chicago.

Merton R.C. (1973). 'Theory of Rational Option Pricing'. *Bell Journal of Economic and Management Science* 4(1), 141–83.

Olsson C. (2002). *Risk Management in Emerging Markets*. Pearson Education: London.

Ong M.K. (2002) ed. *Credit Ratings: Methodologies, Rationale, and Default Risk*. Risk Books: London.

Thomas L.C. (2000). 'A Survey of Credit and Behavioural Scoring: Forecasting Financial Risk of Lending to Consumers'. *International Journal of Forecasting* 16, 149–172.