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TITLE

“Evaluating a model for default risk in non-recourse factoring”

Examination Board

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ABSTRACT

Financial institutions are increasingly trying to improve their services through factoring, where a specialized firm purchases from its clients the trade debts or accounts receivables arising from the sales of goods or the provision of services to trade customers. As total factoring's volume grows rapidly and multiple enterprises and corporations use it as an important source of financing (Factors Chain International, 2009), financial organisations have to use control mechanisms to manage and check their clients and associated risks. While trying to measure risk in factoring, we should not only focus on credit risk, but also on ceding and debtor risk (default risk). However, the research that has been published in this area remains limited and to the best of my knowledge, there is no published model that can support the measurement and management of default risk in non-recourse factoring. Nevertheless, a model for default risk in non-recourse factoring has yet to be assessed, leaving scope for timeliness and novel research. In this dissertation, a model for default risk in non-recourse factoring is introduced as an extension to the normative literature on factoring, which has not paid much attention on risk factors' management. In doing so, the author presents and analyses the indicators that must be considered to assess default risk in non-recourse factoring. These indicators, measured typically at successive times (time series), produce the IoD formula for each debtor. After this, deriving the expected revenue formula, factor may decide if continue to funding this client's debtor. Using this methodology, we rate specific financial indicators, in time series, assessing the default risk in a non-recourse factoring, taking in parallel funding decisions. The proposed approach is significant and novel as it: (a) adds a new dimension to existing poor literature on risk management in factoring and (b) facilitates decision making process in pricing and clients' creditworthiness.

Keywords: Factoring, non-recourse factoring, default risk, credit risk, debtor risk, indicator of default, expecting revenues.

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I owe special thanks and my mental gratitude to my family in supporting me.

"We judge ourselves by what we feel capable of doing, while others judge us by what we have already done"

Henry Wadsworth Longfellow (1807 – 1882)

With sincere appreciation,

to Vassia

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CHAPTER 1

INTRODUCTION

Summary

Financial institutions are increasingly trying to improve their services through factoring, where a specialized firm purchases from its clients the trade debts or accounts receivables arising from the sales of goods or the provision of services to trade customers. As total factoring's volume grows rapidly and multiple enterprises and corporations use it as an important source of financing (Factors Chain International, 2009), financial organisations have to use control mechanisms to manage and check their clients and associated risks. While trying to measure risk in factoring, we should not only focus on **credit risk**, but also on **cedin**g and **debtor risk** (**default risk**). However, the research that has been published in this area remains limited and to the best of my knowledge, there is no published model that can support the measurement and management of default risk in non-recourse factoring. Nevertheless, a model for default risk in non-recourse factoring has yet to be assessed, leaving scope for timeliness and novel research.

In this dissertation, a model for default risk in non-recourse factoring is introduced as an extension to the normative literature on factoring, which has not paid much attention on risk factors' management. In doing so, the author seeks to: (a) highlight the need for the development of a model for default risk in non-recourse factoring, (b) identify the factors which constitute the model and (c) test the proposed model and extend it (if needed). The proposed approach is significant and novel as it: (a) adds a new dimension to existing poor literature on risk management in factoring and (b) facilitates decision making process in pricing and clients' creditworthiness.

This dissertation presents and evaluates a model for default risk in non-recourse factoring, with this chapter introducing the research presented hereunder. The chapter begins by reporting factoring and non-recourse factoring processes, and its increasing need to manage default risk in non-recourse factoring. Section 1.1 briefly introduces the problem area and highlights the importance of a model for default risk in non-recourse factoring, whereas Section 1.2 introduces Default Risk. The aims and the objectives of the dissertation are defined in Section 1.3, with Section 1.4 providing an overview of the research methodology adopted in this research, and Section 1.5 presenting the outline of the dissertation.

1.1 Background to the research problem: factoring and the need for investigating default risk in non-recourse factoring

Soufani (2002) defined factoring as a *"financial process where a specialized firm purchases from its clients the trade debts or accounts receivables arising from the sales of goods or the provision of services to trade customers"*. Factoring is a type of supplier financing in which firms sell their creditworthy accounts receivable at a discount (generally equal to interest plus service fees) and receive immediate cash (Figure 1).

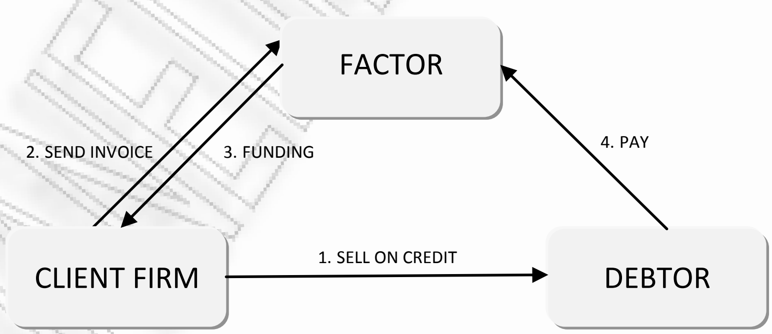

Figure 1: Factoring Process

As presented in Figure 1, there are three types of firms involved in the factoring process, namely: (a) factor, (b) client firm and (c) debtor. The **factor** provides the client firm with specific functions, namely, it substitute cash for accounts receivable, hence placing the client’s extension of credit on a self-liquidating basis as if it was selling for cash. It assumes the credit risk for the accepted accounts and thus takes full responsibility for the solvency of such customers to the extent of the accepted or approved amounts. It also checks the credit and collects the accounts. The **client firm** provides its customers with goods or services for payments on terms. The **debtor** is the one that buys goods and services from the client firm and therefore has the obligation to make the financial payments to the factor within a stipulated period. The aforementioned process can be considered as a form of short-term financing that can potentially improve the working capital positions and alleviate the cash-flow problems of businesses (Klapper, 2006).

Factoring can be done either on a ‘‘non-recourse’’ or ‘‘recourse’’ basis against the factor’s client (the sellers). In non-recourse factoring, the lender not only assumes title to the accounts, but also assumes most of the default risk because the factor does not have recourse against the supplier if the accounts default. Under recourse factoring the factor has a claim (i.e., recourse) against the seller for any account payment deficiency. Therefore, losses occur only if the underlying accounts default and the seller cannot make up the deficiency.

In developed countries it appears that factoring is more frequently done on a non-recourse basis. In Italy, for example, 69% of all factoring is done on a non-recourse basis (Muschella, 2003). Similarly, a study of publicly traded firms in the US found that 73% of firms factored their receivables on a non-recourse basis, but that both sellers with poorer quality receivables and sellers who, themselves, were higher quality were more likely to factor with recourse (Sopranzetti, 1998). Since in emerging markets it is often problematic to assess the default risk of the underlying accounts, typically factoring is done on a recourse basis so that the factor can collect from the seller in the case that the buyer defaults. For instance, a survey of factors in eight EU-accession countries finds that most factoring in the region is done with recourse (Bakker et al., 2004).

It has been reported that factoring has experienced phenomenal growth and has become an important source of financing enterprises and corporations, reaching a worldwide volume of 1,325,111 million euro in 2008 (Factors Chain International, 2009). Despite the International Economical and Financial Crisis, Factors Chain International (2009) indicated that the total world volume for factoring increased in 2008 by 2%, compared to almost 15% in 2007 and that the world total stands in 2009 at €1,325,111 million. Although the importance of factoring varies considerably around the world, it occurs in most countries and is growing especially quickly in developed countries (Figure 2). As presented in Figure 2, factoring is used increasingly by most of the developed economies around the world (Factors Chain International, 2009 & Klapper, 2006).

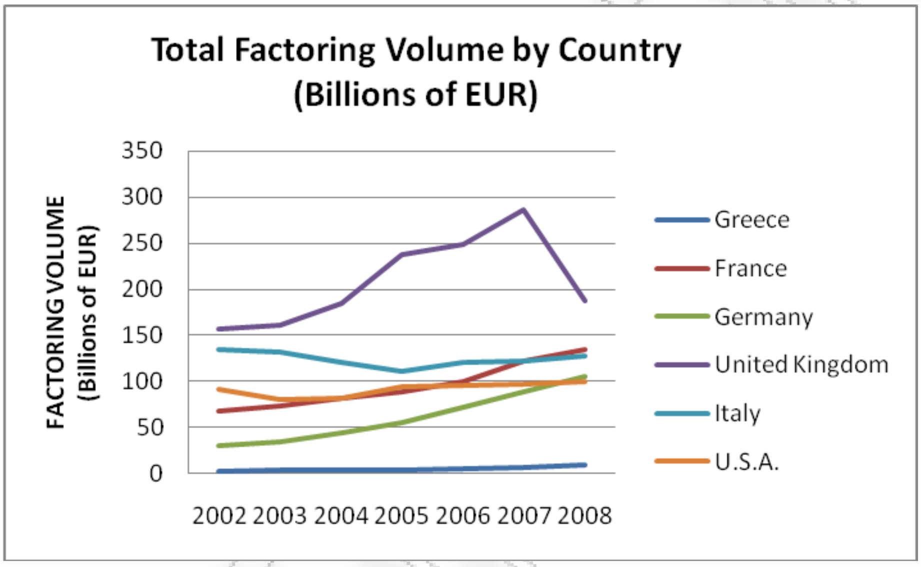

Figure 2. Total Factoring Volume by Country (data from Factors Chain International, 2009)

As factoring grows rapidly and multiple enterprises and corporations use it as an important source of financing, factoring companies have to use control mechanisms to manage and check their clients and associated risks. According to Saunders and Cornett (2008), credit risk seems to be the most important risk and there have been developed and used credit scoring and similar quantitative techniques to evaluate credit risk. These statistical models are used to quantify default probability or default risk classification and include the linear probability model, logit models, and linear discriminant analysis (Saunders and Cornett, 2008). While trying to measure risk in factoring, we should not only focus on credit risk, but also on ceding and debtor risk (default risk). However, in the normative literature not much attention has been paid to the measurement and management of default risk, which appears to be of great importance.

1.2 Default Risk

According to Saunders and Cornett (2008), Default risk is the risk that the borrower is unable or unwilling to fulfill the terms promised under the long contract. It is the uncertainty surrounding a firm's ability to service its debts and obligations. More precisely, default risk in factoring includes both ceding and debtor risk.

The **ceding risk** is the risk represented by the fact that the client does not pay to factor any kind of amount due (funds in use), in the frame of the factoring contract. A ceding risk case will only occur if the client does not fulfill the provisions of the factoring contract or a dispute has been raised and the client is insolvent.

The components of ceding risk are two types of risk that are discriminatory in terms of the economic feasibility of factoring facilities:

1. The financial risk
2. The technical risk

As the financial risk relates to the client's (or prospect) creditworthiness, technical risk seems to be more complicated, as it relates to the daily risks that a factor can encounter in its relationship with its client.

Several types of technical risks exist:

- Fraud risk
- Compensation risk
- Billing risk
- Legal risk
- Handling risk
- Dilution risk
- Commingling risk

The assessment of the ceding risk as a whole, needs not only an appraisal of the quality of the client itself (financial risk), but also the quality of trading between the client and his debtors (technical risk).

The debtor risk is the risk that the debtor does not pay his invoices for creditworthiness reasons. So, it can easily be implied that the assessment of the quality of the debtor (creditworthiness) is mandatory. Through this assessment, the way to manage the risk is established. The management of the debtor risk is divided into two major types of actions:

- Financing decision
- Monitoring of the debtor risk

1.3 Research Aim and Objectives

1.3.1 Research Aim

Hence, the aim of this dissertation is to:

> *Evaluate a model for default risk in non-recourse factoring. In doing so, resulting in the development of an emergent model that will support factoring companies in measuring the risk of pricing their clients and will be used to support decision-making.*

1.3.2 Research Objectives

To reflect upon this aim of this project, a number of specific objectives, which will be analysed hereunder, should be achieved:

Objective 1: Present and analyse the normative literature related to factoring and more specifically to non-recourse factoring.

Objective 2: Propose a novel model for default risk in non-recourse factoring.

Objective 3: Present the research methodology.

Objective 4: Evaluate the proposed model.

Objective 5: To extrapolate conclusions and provide a novel contribution to the domain of default risk in non-recourse factoring.

1.4 Introduction to Research Methodology

To understand the default risk in non-recourse factoring, the author justified the selection of a quantitative research methodology. As the evaluation of a model for default risk in non-recourse factoring, is a relatively new research area, quantitative research appears to be more appropriate to support a deeper understanding of this phenomenon. This is appropriate for the research context under investigation, due to the complex and interrelated nature of the proposed issues under the research of default risk in non-recourse factoring. Moreover, a research strategy with real data was deployed for this dissertation, as it can offer a ‘holistic’ view of the processes involved, as well as a realisation of the topic under research.

1.5 Dissertation Outline

The structure of this dissertation is based on the methodology described by Philips and Pugh (1994). This methodology consists of four elements, namely: (a) background theory, (b) focal theory, (c) data theory and (d) novel contribution. The background theory refers to the literature review, which is conducted to support the identification of the problem domain (Chapter 2). The focal theory is related to the generation of the conceptual model and the research issues (Chapter 3). The third element (data theory) consists of the research design, the data collection methods, the description of the data analysis process and the revised conceptual method and model (Chapters 4, 5 and 6). The fourth element, which is the novel contribution of the dissertation, is presented with conclusions of this research in Chapter 6. In the following paragraphs, the structure of the dissertation is displayed (Figure 2) and the content of each chapter is summarised.

Chapter 1: Introduction

Chapter 1 introduces the research presented in this dissertation and explains the research problem. As a result, the need for identifying and proposing a model that will support the estimation of default risk in non-recourse factoring is analysed. Moreover, the research aims and objectives are presented in Section 1.3 and the dissertation’s outline is explained and displayed diagrammatically.

Chapter 2: Literature Review – Background Theory

In the second chapter, a review of the normative literature is provided. More specifically, the issues related to default risk measurement in factoring are presented. Moreover, the established norms for default risk measurement are discussed and their main limitation are identified and highlighted. In addition, propositions are made.

Chapter 3: Conceptual Development – Focal Theory

In Chapter 3, the conceptual model for default risk in a non-recourse factoring is identified and proposed.

Chapter 4: Methodology and Research Strategy – Data Theory

Based on the aim of this research, Chapter 4 develops an argument for the selection of a suitable research methodology that is going to be used. The reasons for the selection of these methods, their limitations and the way that these limitations are overcome, are explained.

Chapter 5: Empirical Research Data Collection and Analysis – Data Theory

In Chapter 5, the author provides a detailed description of the data carried out to test the conceptual model.

Chapter 6: Conclusions and Further Work – Novel Contribution

In this chapter, the research findings are presented, as well a summary of the research conducted in this dissertation is presented. The novel contribution of this dissertation, as well as the conclusions derived from the findings are also analysed and reported. Furthermore, the chapter highlights possible limitations of this work, describes potential areas of further research, and makes some recommendations for further investigation.

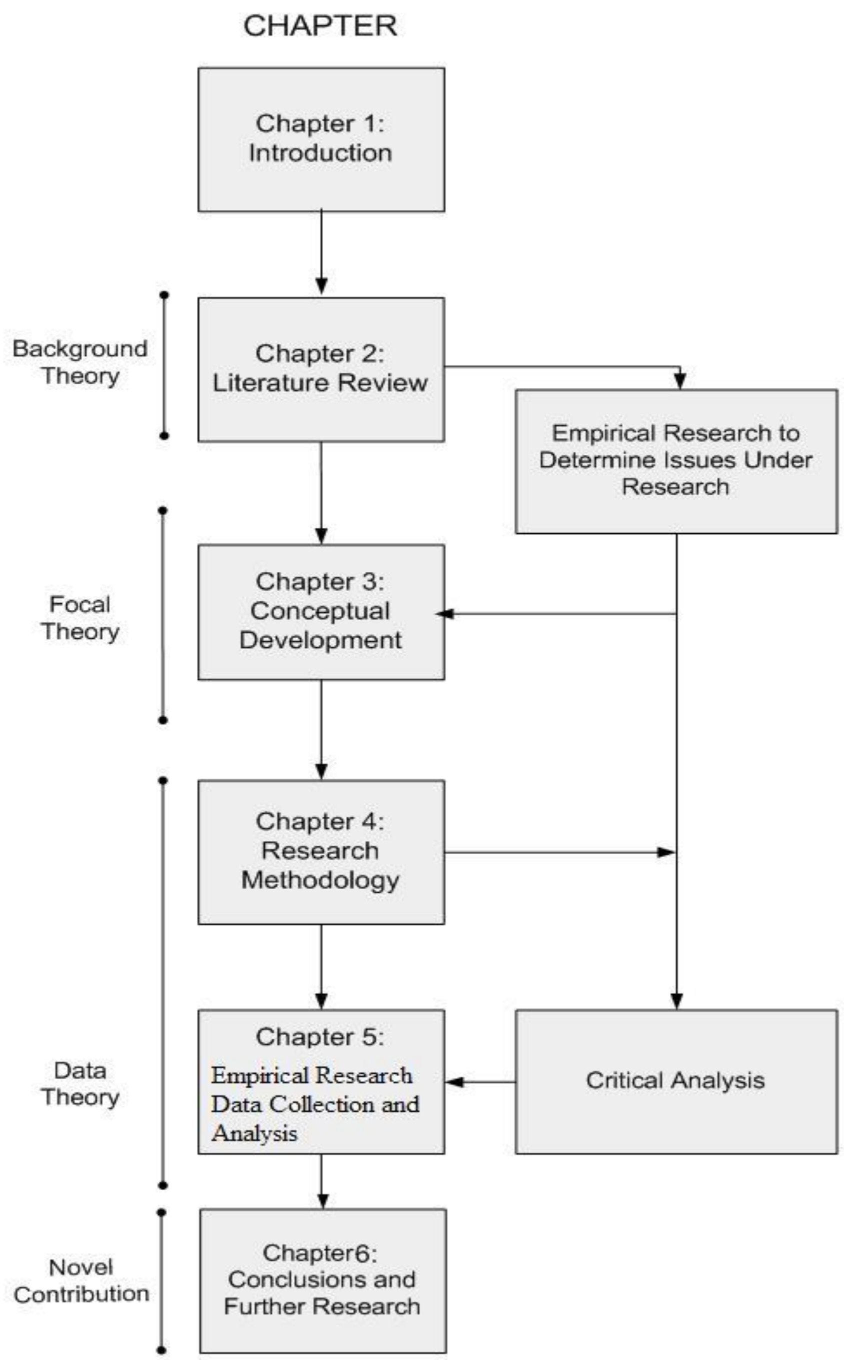

Figure 2: Dissertation Outline

CHAPTER 2

LITERATURE REVIEW

Summary

In this section we describe Moody’s Risk Advisor, which is an expert system developed in close consultation with industry lending experts over a period spanning almost a decade. The system was implemented in Syntel™, a proprietary expert systems language that allows the representation of complex and subtle business concepts in a straightforward manner. Moreover, we present ICAP’s approach, which highlights financial, derogatory and commercial information in order to create a rating indicator. Finally, we reveal why these two models, as well as other techniques used, are inadequate to measure probability of default in non recourse factoring.

2.1 Factoring

A challenge for many small businesses is access to financing. In particular, many firms find it difficult to finance their production cycle, since after goods are delivered most buyers demand 30–90 days to pay. For this duration, sellers issue an invoice, recorded for the buyer as an account payable and for the seller as an account receivable, which is an illiquid asset for the seller until payment is received. Factoring is a type of supplier financing in which firms sell their creditworthy accounts receivable at a discount (generally equal to interest plus service fees) and receive immediate cash. Factoring is not a loan and there are no additional liabilities on the firm's balance sheet, although it provides working capital financing.

Soufani (2002) defined factoring as a *"financial process where a specialized firm purchases from its clients the trade debts or accounts receivables arising from the sales of goods or the provision of services to trade customers"*.

2.1.1 Parties to the Factoring

Factoring is a type of supplier financing in which firms sell their creditworthy accounts receivable at a discount (generally equal to interest plus service fees) and receive immediate cash (Figure 1). As presented in Figure 1, there are three types of firms involved in the factoring process, namely: (a) factor, (b) client firm and (c) debtor.

The **factor** provides the client firm with specific functions, namely, it substitute cash for accounts receivable, hence placing the client's extension of credit on a self-liquidating basis as if it was selling for cash. It assumes the credit risk for the accepted accounts and thus takes full responsibility for the solvency of such customers to the extent of the accepted or approved amounts. It also checks the credit and collects the accounts. The **client firm** provides its customers with goods or services for payments on terms. The **debtor** is the one that buys goods and services from the client firm and therefore has the obligation to make the financial payments to the factor within a stipulated period. The aforementioned process can be considered as a form of short-term financing that can potentially improve the working capital positions and alleviate the cash-flow problems of businesses (Klapper, 2006).

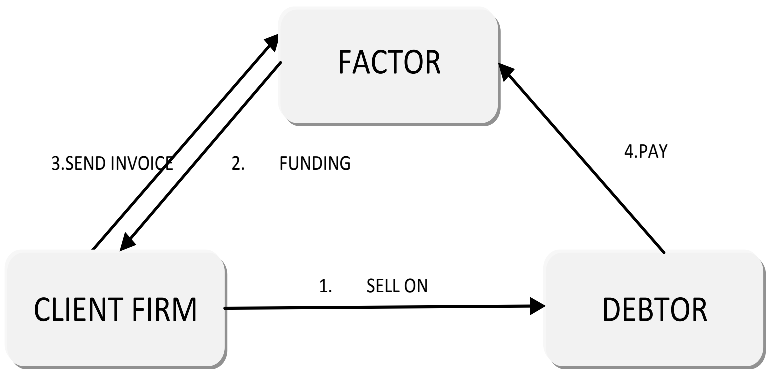

Figure 3: Factoring Process

2.1.2 Mechanism of Factoring

As presented in Figure 1, factoring is generated by credit sales in the normal course business. The main function of factor is the realisation of sales. Once the transaction takes place, the role of factor step in to realise the sales/collect receivables. Thus, factor act as an intermediary between the client firm and the debtor. In factoring, the underlying assets are the client firm's accounts receivable, which are purchased by the factor at a discount. The remaining balance is paid to the seller when the receivables are paid to the factor, less interest and service fees. For example, a factor might offer sellers financing up to 70% of the value of an account receivable and pay the remaining 30% – less interest and service fees – when payment is received from the buyer. The advance rate will be determined in part by historical payment patterns, which may vary by country and firm.

The mechanism of factoring is summed up as below:

i. An agreement is entered into between the client firm and the factor. The agreement provides the basis and the scope understanding reached between the two for rendering factor service.

ii. The sales documents should contain the instructions to make payment directly to the factor who is assigned the job of collection of receivables.

iii. When the payment is received by the factor, the account of the firm is credited by the factor after deducting its fees, charges, interest etc. as agreed.

iv. The factor may provide advance finance to the selling firm conditions of the agreement so require.

2.2 Factoring Services

Factoring can be viewed as a bundle of activities. It is the most comprehensive type of factoring arrangement offering all types of services, namely: (a) Finance, (b) Sales ledger administration, (c) Collection, (d) Debt protection, and (e) Advisory services.

- **Finance,** which is the lifeblood of a business, is made available easily by the factor to the client. A factor purchases the book debts of his client and debts are assigned in favor of the factor. 75% to 80 percent of the assigned debts is given as an advance to the client by the factor.
  a. Where an agreement is entered into between the client (seller) and the c factor for the purchase of receivables without recourse, the factor becomes responsible to the seller on the due date of the invoice whether or not the buyer makes the payment to the factor.
  b. Where the debts are factored with recourse- the client has to refund the full finance amount provided by the factor in case the buyer fails to make the payment on due date.
- The **Sales ledger administration services** involve assessing the creditworthiness of the seller’s customers whose accounts the factor will

purchase. Factors typically base this assessment on a combination of their own proprietary data and publicly available data on account payment performance.

- The **Collection services** involve the activities associated with collecting delinquent accounts and minimizing the losses associated with these accounts. This includes notifying a buyer that an account is delinquent (i.e., past due) and pursuing collection through the judicial system. Factoring allows SMEs to effectively outsource their credit and collection functions to their factor. This represents another important distinction between factors and traditional commercial lenders.
- The **Debt protection service** is provided where the debts are factored without recourse. The factor fixes the credit limits (i.e. the limit up to which the client can sell goods to customers) in respect of approved customers. Within these limits the factor undertakes to purchase all trade debts and assumes risk of default in payment by the customers. The factor not only relieves the client from the collection work but also advises the client on the creditworthiness of potential customers. Thus the factor helps the client in adopting better credit control policy. The credit standing of the customer is assessed by the factors on the basis of information collected from credit rating reports, bank reports, trade reference, financial statement analysis and by calculating the important ratios in respect of liquidity and profitability position.
- **Advisory services** arise out of the close relationship between a factor and a client. Since the factors have better knowledge and wide experience in field of finance, and possess extensive credit information about customer's standing, they provide various advisory services on the matters relating to:
  a. Customer's preferences regarding the clients' products.
  b. Changes in marketing policies/strategies of the competitors.
  c. Suggest improvements in the procedures adopted for invoicing, delivery and sales return.
  d. Helping the client for raising finance from banks/financial institutions, etc.

2.3 Factoring Types

A number of factoring arrangements are possible depending upon the agreement reached between the credit firm and the factor (explained above). The most common feature of practically all the factoring transactions is collection of receivables and administration of sale ledger. However, **following are some of the important types of factoring arrangements:**

2.3.1 Recourse vs Non - recourse Factoring

Factoring can be done either on a ‘‘non-recourse’’ or ‘‘recourse’’ basis against the factor’s client. In non-recourse factoring, the lender not only assumes title to the accounts, but also assumes most of the default risk because the factor does not have recourse against the supplier if the accounts default. Under recourse factoring the factor has a claim (i.e., recourse) against the seller for any account payment deficiency. Therefore, losses occur only if the underlying accounts default and the seller cannot make up the deficiency. In developed countries it appears that factoring is more frequently done on a non-recourse basis. Since in emerging markets it is often problematic to assess the default risk of the underlying accounts, typically factoring is done on a recourse basis so that the factor can collect from the seller in the case that the buyer defaults. For instance, a survey of factors in eight EU-accession countries finds that most factoring in the region is done with recourse (Bakker et al., 2004).

An important feature of the factoring relationship is that a factor will typically advance less than 100% of the face value of the receivable even though it takes ownership of the entire receivable. The difference between this advance amount and the invoice amount (adjusted for any netting effects such as sales rebates) creates a reserve held by the factor. This reserve will be used to cover any deficiencies in the payment of the related invoice as well as all credit memos and adjustments (e.g., returned items, advertising allowances, discounts, etc.). Thus, even in non-recourse factoring there is risk sharing between the factor and the client in the form of this reserve account.

2.3.2 Notification or non-notification basis

Factoring can also be done on either a notification or non-notification basis. Notification means that the buyers are notified that their accounts (i.e., their payables) have been sold to a factor. Under notification factoring, the buyers typically furnish the factor with delivery receipts, an assignment of the accounts and duplicate invoices prepared in a form that indicates clearly to the supplier that their account has been purchased by the factor.

2.3.3 ‘‘Reverse factoring”

In ordinary factoring, a small firm sells its complete portfolio of receivables, from multiple buyers, to a single factor. Many factors will only purchase complete portfolios of receivables in order to diversify their risk to any one seller. In fact, many factors require sellers to have a minimum number of customers in order to reduce the exposure of the factor to one buyer – and to the seller’s ability to repay from receipts from other buyers – in the case that a buyer defaults. However, this diversified portfolio approach requires factors to collect credit information and calculate the credit risk for many buyers.

Ordinary factoring has in general not been profitable in emerging markets. First, if good historical credit information in unavailable, then the factor takes on a large credit risk. For instance, in many emerging markets, the credit information bureau is incomplete (i.e., may not include small firms) or non-bank lenders, such as factors, are prohibited from joining. Second, fraud is a big problem in this industry – bogus receivables, nonexisting customers, etc. – and a weak legal environment and non-electronic business registries and credit bureaus make it more difficult to identify these problems. An alternative often used in emerging markets is for the factor to buy receivables ‘‘with recourse’’, which means that the seller is accountable in the case that a buyer does not pay its invoice, and that the seller of the receivables retains the credit risk. However, this may not successfully reduce the factor’s exposure to the credit risk of the seller's customers, since in the case of a customer's default, the seller may not have sufficient capital reserves to repay the factor.

One solution to these barriers to factoring is the technology often referred to as ''Reverse Factoring''. In this case, the lender purchases accounts receivables only from specific informationally transparent, high-quality buyers. The factor only needs to collect credit information and calculate the credit risk for selected buyers, such as large, internationally accredited firms. Like traditional factoring, which allows a supplier to transfer the credit risk of default from itself to its customers, the main advantage of reverse factoring is that the credit risk is equal to the default risk of the high-quality customer, and not the risky SME. This arrangement allows creditors in developing countries to factor ''without recourse'' and provides low-risk financing to high-risk suppliers.

Reverse factoring may be particularly beneficial for SMEs for a number of reasons. First, as previously discussed, ordinary factoring requires comprehensive credit information on all the seller's customers, which may be particularly difficult and costly to determine for SMEs in countries with weak credit information systems. Second, reverse factoring makes it possible for firms to factor without recourse, which allows SMEs to transfer their credit risk to the factor.

Another advantage of reverse factoring is that it provides benefits to lenders and buyers as well. In many countries factoring is offered by banks. In this case, factoring enables lenders to develop relationships with small firms (with high quality customers) without taking on additional risk. This may provide cross-selling opportunities and allows the lender to build a credit history on the small firm that may lead to additional lending (for fixed assets, for example).

The large buyers may also benefit: by engineering a reverse factoring arrangement with a lender and providing its customers with working capital financing, the buyer may be able to negotiate better terms with its suppliers. For example, buyers may be able to extend the terms of their accounts payable from 30 to 60 days. In addition, the buyer benefits from outsourcing its own payables management (e.g., the buyer can send a payment to one lender rather than many small suppliers). Many buyers favor this arrangement to self-financing receivables, such as making early payments at a discount, since it might be difficult in countries with weak legal environments to receive back payments in the case that goods are damaged and returned.

2.4 Volume of Factoring

Empirical evidence indicates that factoring is used in both developed and developing countries. It has been known amongst business and finance professionals for a while in the US, Europe and Japan and does not require a very specific legal framework to be promoted (ADBI, 2006). Factoring has been rapidly growing due to private initiatives in some of the developing and transitional countries, to support and complement banking services. In addition, factoring has experienced phenomenal growth and has become an important source of financing enterprises and corporations, reaching a worldwide volume of 1,325,111 million euro in 2008 (Factors Chain International, 2009).

Despite the International Economical and Financial Crisis, Factors Chain International (2009) indicated that the total world volume for factoring increased in 2008 by 2%, compared to almost 15% in 2007 and that the world total stands in 2009 at €1,325,111 million. Although the importance of factoring varies considerably around the world, it occurs in most countries and is growing especially quickly in developed countries (Figure 2). As presented in Figure 2, factoring is used increasingly by most of the developed economies around the world (Factors Chain International, 2009 & Klapper, 2006).

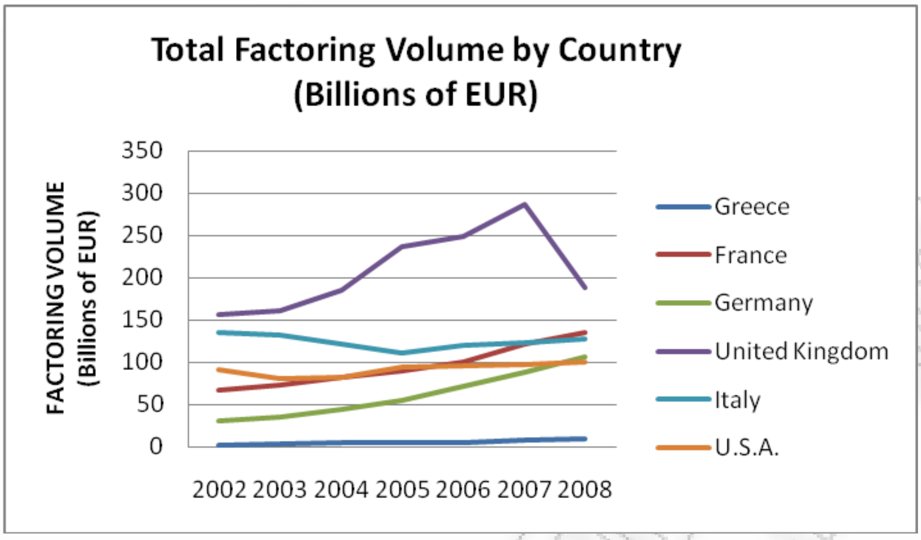

Figure 4. Total Factoring Volume by Country (data from Factors Chain International, 2009)

Factoring is explicitly linked to the value of a supplier's accounts receivable and receivables are sold, rather than collateralized, and factored receivables are not part of the estate of a bankrupt firm. Therefore, factoring may allow a high-risk supplier to transfer its credit risk to higher quality buyers. Empirical tests find that factoring is larger in countries with greater economic development and growth and developed credit information bureaus.

2.5 Factoring: Advantages and Disadvantages

2.5.1 Advantages of Factoring

Around the world, factoring is a growing source of external financing for large corporations and SMEs. Factoring is quite distinct from traditional forms of commercial lending where credit is primarily underwritten based on the creditworthiness of the seller rather than the value of the seller's underlying assets. In a traditional lending relationship, the lender looks to collateral only as a secondary source of repayment. The primary source of repayment is the seller itself and its viability as an ongoing entity.

What is unique about factoring is that the credit provided by a lender is explicitly linked on a formula basis to the value of a supplier’s accounts receivable and is less dependent on the supplier’s overall creditworthiness.

Therefore, factoring may allow high-risk suppliers to transfer their credit risk to their high-quality buyers. Factoring appears to be a powerful tool in providing financing to high-risk informationally opaque sellers. Its key virtue is that underwriting in factoring is based on the risk of the accounts receivable themselves rather than the risk of the seller. For example, factoring may be particularly well suited for financing receivables from large or foreign firms when those receivables are obligations of buyers who are more creditworthy than the seller itself.

Factoring may also be particularly attractive in financial systems with weak commercial laws and enforcement. Like traditional forms of commercial lending, factoring provides small and medium enterprises (SMEs) with working capital financing. However, unlike traditional forms of working capital financing, factoring involves the outright purchase of the accounts receivable by the factor, rather than the collateralization of a loan. The virtue of factoring in a weak business environment is that the factored receivables are removed from the bankruptcy estate of the seller and become the property of the factor.

Factoring is becoming popular all over the world on account of various services offered by the institutions engaged in it. Factors render services ranging from bill discounting facilities offered by the commercial banks to total takeover of administration of credit sales including maintenance of sales ledger, collection of accounts receivables, credit control, protection from bad debts, provision of finance and rendering of advisory services to their clients. Thus factoring is a tool of receivables management employed to release the funds tied up in credit extended to customers and to solve problems relating to collection, delays and defaults of the receivables.

A firm that enters into factoring agreement is benefited in a number of ways, some of the important benefits are outlined below:

- The factors provides specialised services with regard to sales ledger administration and credit control and relieves the client from the botheration of debt collection. He can concentrate on the other major areas of his business and improve his efficiency.
- The advance payments made by the factor to the client in respect of the bills purchased increase his liquid resources. He is able to meet his liabilities as and when they arise thus improving his credit standing position before suppliers, lenders and bankers. The factor's assumption of credit risk relieves him from the tension of bad debt losses. The client can take steps to reduce his reserve for bad debts.
- It provides flexibility to the company to decide about extending better terms to their customers.
- The company itself is in a better position to meet its commitments more promptly due to improved cash flows.
- Enables the company to meet seasonal demands for cash whenever required.
- Better purchase planning is possible. Availability of cash helps the company to avail cash discounts on its purchases.
- As it is an off balance sheet finance, thus it does not affect the financial structure. This would help in boosting the efficiency ratios such as return on asset etc.
- Saves the management time and effort in collecting the receivables and in sales ledger management.
- Where credit information is also provided by the factor, it helps the company to avoid bad debts.
- It ensures better management of receivables as factor firm is specialised agency for the same. The factor carries out assessment of the client with regard to his financial, operational and managerial capabilities whether his debts are collectable and viability of his operations. He also assesses the debtor regarding the nature of business, vulnerability of his operations; and assesses the debtor regarding the nature of business, vulnerability to seasonality, history of operations, the term of sales, the track record and bank report available on the past history.

2.5.2 Disadvantages of Factoring

The above listed advantages do not mean that the factoring operations are totally free from any limitation. The attendant risk itself is of very high degree. Some of the main limitations of such transactions are listed below:

- It may lead to over-confidence in the behavior of the client resulting in over-trading or mismanagement.
- The risk element in factoring gets accentuated due to possible fraudulent acts by the client in furnishing the main instrument "invoice" to the factor.
- Invoicing against nonexistent goods, pre-invoicing (i.e. invoicing before physical dispatch of goods), duplicate-invoicing (i.e. making more than one invoice in respect of single transaction) are some commonly found frauds in such operations, which had put many factors into difficulty in late 50's all over the world.
- Lack of professionalism and competence, underdeveloped expertise, resistance to change etc. are some of the problems which have made factoring services unpopular.
- Rights of the factor resulting from purchase of trade debts are uncertain, not as strong as that in bills of exchange and are subject to settlement of discounts, returns and allowances.
- Small companies with lesser turnover, companies having high concentration on a few debtors, companies with speculative business, companies selling a large number of products of various types to general public or companies having large number of debtors for small amounts etc. may not be suitable for entering into factoring contracts.

However, factoring may still be hampered by weak contract enforcement institutions and other tax, legal, and regulatory impediments. Weaker governance structures may also create additional barriers to the collection of receivables in developing countries. For instance, it might be more difficult to collect receivables from state-owned companies (i.e., where state-owned companies are the buyers) then from other companies. Factors may also face difficulties collecting receivables from multi-nationals and foreign buyers.

2.6 Credit risk analysis in a non - recourse factoring

As factoring grows rapidly and multiple enterprises and corporations use it as an important source of financing, factoring companies have to use control mechanisms to manage and check their clients and associated risks. According to Saunders and Cornett (2008), credit risk seems to be the most important risk and there have been developed and used credit scoring and similar quantitative techniques to evaluate credit risk. The presented models are used to quantify default probability or default risk classification and include the linear probability model, logit models, and linear discriminant analysis (Saunders and Cornett, 2008). **While trying to measure risk in factoring, we should not only focus on credit risk, but also on ceding and debtor risk (default risk).** However, in the normative literature not much attention has been paid to the measurement and management of default risk, which appears to be of great importance.

2.7 The gap: Measuring risk in factoring

As factoring companies participate in financial processes, it is evident that they must measure the risk taking when a contract is signed. As in a recourse contract, the factor has a claim (i.e., recourse) against the seller for any account payment deficiency, in non recourse factoring matters are more complicated. More specifically, in non recourse factoring there is a need to measure the risk taken over debtors and find the cohesion among them, in order to express it in a common rating. We have to focus on two main variables which are of high importance when we measure risk in nonrecourse factoring. The first variable is time (claims are open for 30 to 90 days). The second one is the risk taken, as factor takes the risk over the debtors.

Nowadays, there are no precise models for measuring risk in factoring companies. Therefore, factoring companies use credit risk models that are used by financial institutions all over the world. These credit risk advisors are presented in the following paragraphs.

2.8 Credit Risk Advisors in Financial Institutions

Credit risk assessment is a key component in the process of commercial lending. A potential borrower's credit assessment determines whether the borrower will ultimately be granted credit, and if so at what cost in terms of underwriting fees and interest levels. Although many methods exist for evaluating credit risk (Antonov 2000; Falkenstein, Boral et al. 2000), for many lenders, risk assessment in the underwriting process is fundamentally different from the evaluation of credits already within a portfolio due to differing levels of analytic detail, opportunity costs and analytic objectives. In this section, we present: (a) ICAP’s model and (b) Moody’s Risk Advisor (MRA), as well as the procedures followed in statistical and scorecard models.

2.8.1 ICAP model

ICAP has proposed for measuring risk a model that consists of the following categories of variables (a) Financial Information, (b) Derogatory Information and (c) Commercial Information. In each category the author has identified multiple variables that should be considered.

It is rather a domestic model, as it bases on ICAP Databank, which includes financial information about greek enterprises. Moreover, the weights of each variable are not disposable in order to have a precise view of the technical structure of the model.

2.8.1.1 Financial Information

The assessment of financial variables for private companies is performed separately as the objective is to test their ability to predict credit risk and to detect the variables with the highest predictive power. For the appropriate assessment of this type of data, financial ratios are chosen instead of the main figures taken from financial statements because financial ratios determine directly the financial standing of the private companies.

Financial ratios are classified into the following groups:

- Profitability
- Liquidity
- Capital structure
- Activity

For the evaluation of financial data, 26 static financial ratios, and 11 dynamic ratios were created.

Static Ratios			
1	Profit Before Income and Tax / Shareholders Equity	16	Collection Period: 365 * Trade Receivables Bills / Net Sales
2	(Profit Before Income and Tax + Interest Expenses) / Capital Employed		Collection Period: 365 * Trade Receivables Bills / (Net Sales + Commissions and Other Operating Income)
3	Profit Before Income / Capital Employed		Collection Period: 365 * Trade Receivables Bills (included taxes) / Net Sales
4	Gross Profit Margin / Net Sales		Collection Period: 365 * Trade Receivables Bills (included taxes) / (Net Sales + Commissions and Other Operating Income)
5	Operating Profit Margin / (Net Sales + Commissions and Other Operating Income)	17	Payable Period: 365 * Trade Payable / Cost of Sales
6	(Profit Before Income and Tax + Interest Expenses) / (Net Sales + Commissions and Other Operating Income)		Payable Period: 365 * Trade Payable (included taxes) / Cost of Sales
7	Profit Before Income and Tax / (Net Sales + Commissions)	18	365* Inventories / Cost of Sales
8	Net Sales + Commissions / Capital Employed	19	Shareholders Equity / Current Liabilities and Net worth
9	Net Sales + Commissions / Shareholders Equity	20	Capital Employed / Current Liabilities and Net worth
10	(Shareholders Equity + Medium long term debt + Provisions) / [Net Fixed Assets - (Long Term Receivables + Participations)]	21	Interest Expenses / Net Sales
11	(Medium Long Term Debt + Provisions + Current Liabilities) / Shareholders Equity	22	(Machinery Equipment Depreciation + Building Installation Depreciation + Intangibles Depreciation) / (Machinery and Equipment + Buildings Installations + Intangibles)
12	(Profit Before Income and Tax + Interest Expenses) / Interest Expenses	23	365 * (Capital Employed – Net fixed Assets) / Net Sales
13	Shareholders Equity / Capital Employed	24	365*(Inventories + Receivables – Current Liabilities + Short Term Bank Debt) / Net Sales
14	Cash Deposits + Receivables + Inventories / Current Liabilities	25	[365*(Capital Employed – Net fixed Assets) / Net Sales] – [365 *(Inventories + Receivables – Current Liabilities + Short Term Bank Debt) / Net Sales]
15	Cash Deposits + Receivables / Current Liabilities	26	Logarithm of Sales

Dynamic Ratios	
1	Percentage Change of Turnover
2	[Current Assets / Net Sales $_{(year\ T)}$]– [Current Assets / Net Sales $_{(year\ T\text{-}1)}$]
3	[Net Fixed Assets / Net Sales $_{(year\ T)}$] – [Net Fixed Assets / Net Sales $_{(year\ T\text{-}1)}$]
4	[365* Trade Receivables / Net Sales] $_{(year\ T)}$ – [365* * Trade Receivables / Net Sales] $_{(year\ T\text{-}1)}$
5	[365*Trade Payable / Cost of Sales] $_{(year\ T)}$ - [365* Trade Payable / Cost of Sales] $_{(year\ T\text{-}1)}$
6	[Gross Margin / Net Sales $_{(year\ T)}$]– [Gross Margin / Net Sales $_{(year\ T\text{-}1)}$]
7	[Short Term Bank Debt/Total Assets $_{(year\ T)}$]– [Short Term Bank Debt/Total Assets $_{(year\ T\text{-}1)}$]
8	Percentage Change of Net Fixed Assets
9	Percentage Change of Inventories
10	Change of Depreciation ratio
11	Percentage Change of Gross Margin

For the evaluation of financial data for SA, LLC, SSLLC with published financial data and Net Sales or Total Assets lower than 10,000€, the input variables are the following: Shareholders Equity, Shareholders Equity to Current Liabilities and Net Worth, Profit Before Income and Tax, Shareholders Equity to Share Capital and Sales.

Furthermore, the financial data for GP, LP, SP is limited to the reported Sales, while for SA, LLC, SSLLC without published balance sheet no financial data are assessed.

2.8.1.2 Derogatory Information

For the assessment of derogatory data, information gathered from government gazettes or from first instance courts, is being employed. This information includes (a) type of delinquency, (b) total value of delinquencies divided by Net Sales, (c) the number of delinquencies according to the type of data, (d) the year when delinquency occurred and (e) the percentage of settled delinquencies.

Likewise in the case of financial data, the derogatory information, is evaluated by a separate model. The evaluation of the derogatory information is performed for (a) SA, LLC, SSLLC with published balance sheet, (b) SA, LLC, SSLLC without published balance sheet and for (c) GP, LP, SP.

2.8.1.3 Commercial Information

The derogatory information and the results of the financial data process (where applicable) are combined with the commercial data in the final model. The final models are distinguished in SA, LLC, SSLLC with published balance sheet (industry, trade, services), SA, LLC, SSLLC without balance sheet and GP, LP, SP and classify the companies in the 10 credit ratings developed by ICAP.

The variables examined are the following: (1) number of collaborated banks (2) years of operation (3) number of premises (4) staff (5) geographical area (6) activity sector

(7) imports (8) exports (9) representations (10) listing in Athens Exchange S.A (11) legal status, etc.

2.8.2 Moody's Risk Advisor (MRA) Analysis

One of the most used credit risk advisors, which is currently used by organisations around the world, including large commercial banks such as Barclays, Lloyds, and EDC, is Moody’s Risk Advisor (MRA). We should note that MRA is used to offer credit risk analysis not only by factoring companies, but also by financial institutions in general. MRA will be analysed in the following paragraphs.

The system is unique in that it can complement statistical models of default by including both quantitative information and the non-quantitative, often subjective, information that typifies the underwriting process at many institutions. The knowledge-based system (KBS) is also unique from a technical perspective in that declarative functions are used instead of production rules to represent knowledge.

Since each institution has its own policies and underwriting practices it is not uncommon for firms to need to customise a system to account for differences in business lines or changing economic or regulatory environments. This allows experts within an institution to impart their experience and foresight into the system. Accordingly, a decision support system needs to be flexible and customisable enough to fit in with the business practices and environment of its users. The system must be able to interface not only with end-users, but other systems in use within the institution. These dimensions are summarised in the table below. The second column shows that an ideal solution should possess at least the level of support for each attribute shown.

Attribute	Ideal Solution
Accuracy	HIGH
Explainability	HIGH
Tolerance for Noisy Data	MODERATE
Tolerance for Sparse Data	MODERATE
Tolerance for complexity	HIGH
Response Speed	MODERATE
Flexibility	HIGH
Embedability	HIGH

Table 1. MRA system's dimensions

Moody's Risk Advisor, is a knowledge-based system (KBS) for supporting the underwriting process. A KBS is a computer program that encapsulates expertise, elicited from experts in the form of business concepts and the relationships between them. The expertise within MRA was compiled over almost a decade by bankers and credit experts from a variety of institutions. The system is implemented in a proprietary expert systems language called Syntel™.

Knowledge representation, as it is used for MRA, is best understood as a one directional network of decision-components (nodes) that are arranged hierarchically from the most general assessment of risk (i.e. Borrower Risk Assessment) to the most specific (financial statement values such as interest expense, etc. and user subjective inputs). In the current implementation of the MRA knowledge-base, the main network forms a tree in which the raw data enter at the bottom and assessments are produced to illuminate key business concepts through the tree, culminating in the pinnacle (root) node.

Working backward from the root (Borrower Rating) node, the lower layers of the network represent various sub-assessments (e.g., Financial Assessment, Subjective Assessment, etc.) with a similar structure: an assessment being derived from combinations of lower nodes. This pattern repeats itself recursively until a node is reached that represents an input value.

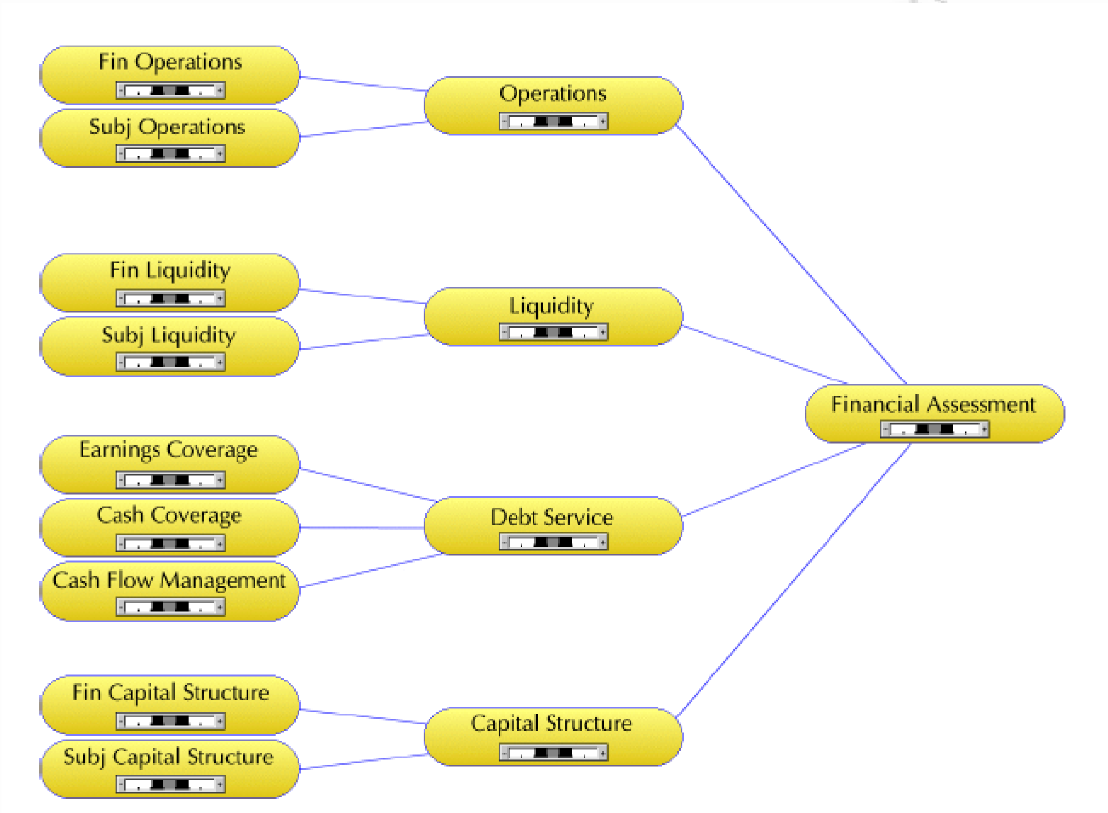

Figure 5. The structure of the assessment network used to calculate the Financial Assessment

Figure 5 shows how the various components of the Financial Assessment are combined. Sub-assessments for each component of the analysis are weighted and combined using expert rules. This representation makes the knowledge base more readily understandable to credit professionals and allows them to understand the dynamics of the model.

In addition, Figure 5 shows the various components of the Financial Assessment component of the MRA knowledge base. Note how each sub-component feeds into a more abstract concept within the knowledge base. Similarly, each of the sub-components shown, derive from more basic concepts, eventually starting with raw data. For example, the Debt Service Coverage Assessment in Figure 5 can be further broken down to its base components as shown in Figure 6, below.

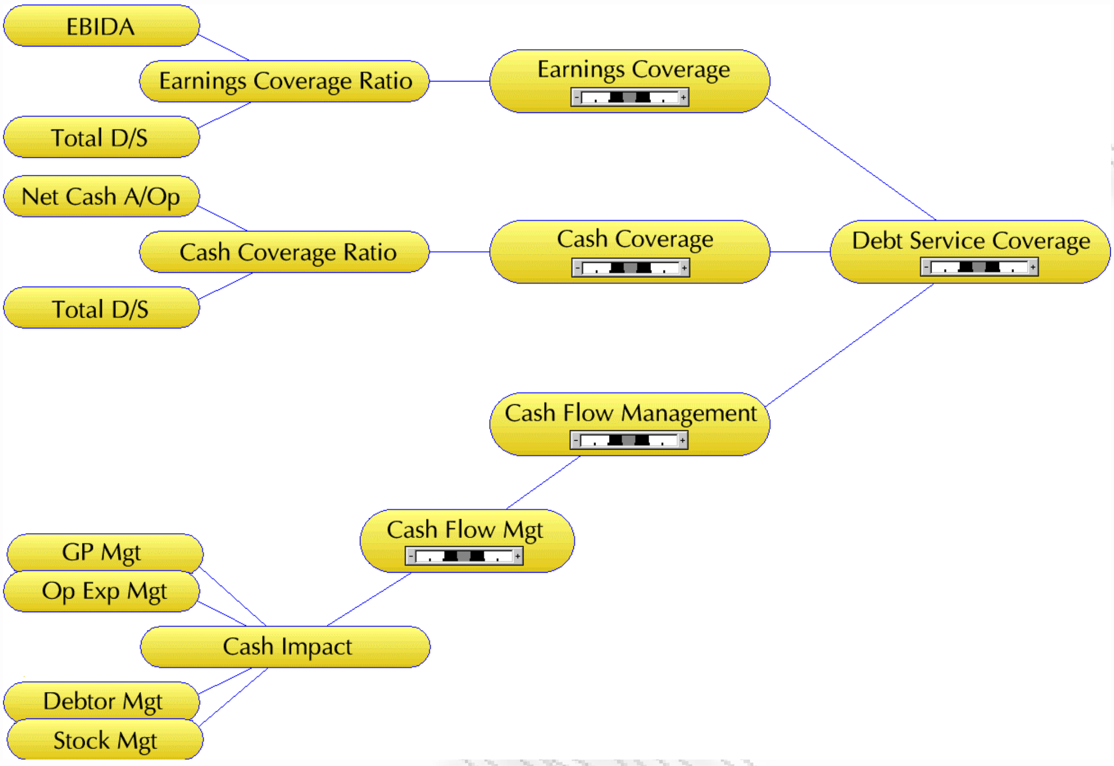

Figure 6. The structure of the assessment network used to calculate the Debt Service Coverage Assessment

Figure 6 shows a close up of the details of the components of the Debt Service sub-assessment pictured in Figure 5. In some cases, the schematic terminates at an input such as EBIDA (upper left). In others, such as Stock Mgt., still lower levels exist below the one shown.

The Syntel™ language used to create MRA supports a wide range of functions that can be used to represent expert knowledge. These include logical, arithmetic, statistical and aggregation functions as well as rules. Many of these are used to assess the inputs to MRA. For example, the assessment of all non-Debt Service ratios in MRA consists of a procedure that requires the calculation of several factors including the ratio’s historic trend, its volatility and an estimate of how the value of the ratio under analysis ranks within its industry group.

In addition Syntel™ supports a powerful function called WEIGHT that is used throughout MRA. WEIGHT supports a concise representation of expert knowledge. WEIGHT takes one or more nodes as inputs and calculates an assessment of those inputs. For each input a weight rule is coded. The weight rule specifies a mapping from the input's value to a numeric vote that constitutes the input's contribution to the WEIGHT node's value. The contributions of the inputs are summed and then converted into a utility value. This value is then mapped into the WEIGHT node's type to produce an output value. The rule, is thus a type of lookup-table parameterized with expert knowledge.

To illustrate the concept, consider a fictional quantitative input variable. If, as part of the management assessment, MRA had a question for the size of the management team, expert knowledge about the management team size could be encoded in a weight rule as shown in the following table:

Fixed Point	Votes
1	-20
5	40
8	0
15	-40

Table 2. MRA weight rules (fixed points)

Experts would first specify a series of fixed points with associated votes. If the rule feeds the Management Quality component, then the rule can produce positive and negative votes, which move the score for the Management attribute upward or downward. For example, a single manager would tend to reduce the score, while a small team of five would increase it, but a larger team of 15 would decrease it.

For values between the fixed points, the system interpolates votes linearly for intermediate values. For example, if the actual management team consisted of four individuals then the vote for this attribute would be computed 13 as 25.

From a practical perspective, this method is extremely useful since it means that bankers can speak in terms they are comfortable with and these terms can be translated into Syntel™ and included in MRA.

In the next section, we give an example of the definition and application of a weight rule. These rules are used extensively in MRA and are especially useful for dealing with subjective inputs.

Handling Non-numeric and Subjective variables

In the previous section, we discussed conceptually how MRA aggregates quantitative information. Unfortunately, not all information that an analyst might wish to include in his analysis can be boiled down to simple ratios. What about things like management quality or industry competitiveness? How should these business concepts be addressed?

In order to reconcile the often incompatible scales (e.g., ordered classes, unordered-discrete, continuous, etc.) and orders of magnitude (e.g., dollars and ratios or dollars and "GOOD MANAGEMENT") of different inputs, all assessments in MRA are internally represented as utilities (in the economics sense of measures of goodness). The utilities are mapped back and forth between discrete and continuous representations on arbitrary scales to facilitate understanding by the user.

For example, consider the case of the concept "MANAGEMENT QUALITY." Most bankers would agree that this is an important variable but would have difficulty describing it quantitatively. Rather they might discuss it in terms of the relative merits of different aspects of the management team and assign these a qualitative value based on their opinions. Figure 5 illustrates MRA's approach.

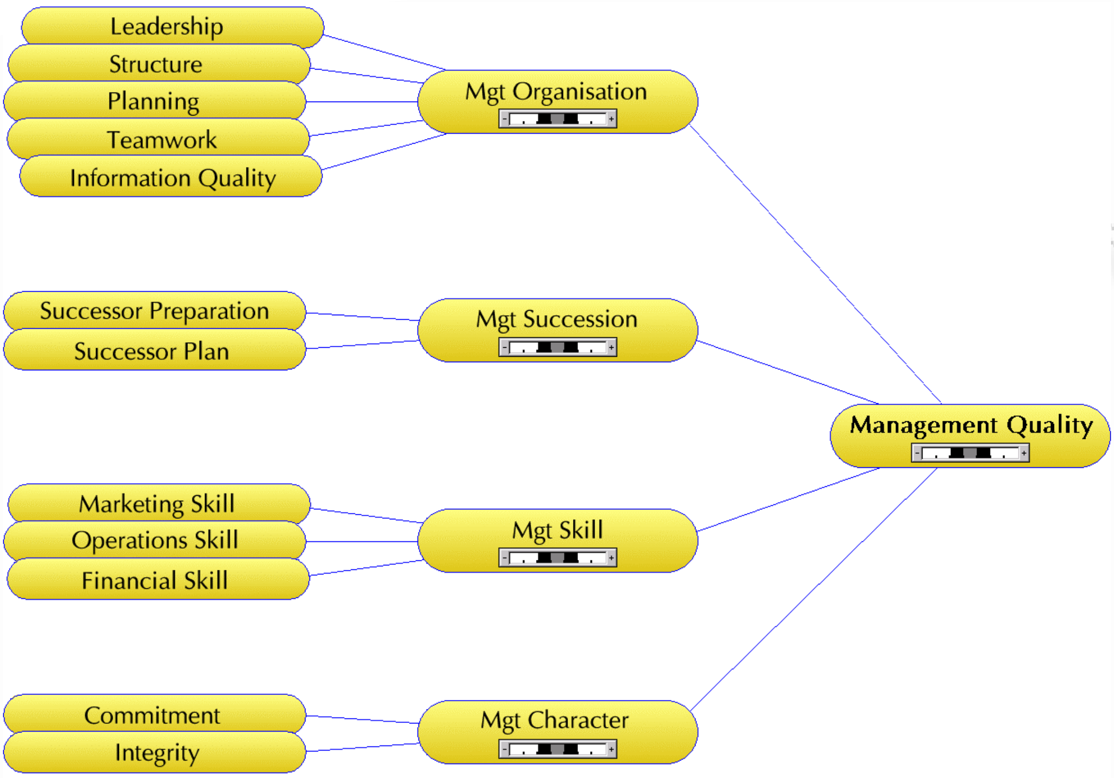

Figure 7. The structure of the assessment network used to calculate the Management Quality Assessment

MRA can incorporate both subjective and quantitative data. The assessment of Management Quality shows schematically how subjective elements are combined. Management Quality concept is broken down into four sub-components: Organisation, Succession, Skill and Character and these in turn are broken down further. MRA takes the approach that such complex values are very difficult to assess with a single input. Instead the Management Quality concept is broken down into four sub-components: Organisation, Succession, Skill and Character and these in turn are broken down further. This simplifies the user’s task as less needs to be considered when making an evaluation for each input and improves the consistency of such subjective assessments as Management Quality; for each borrower the user will consider the same factors and these will be evaluated in a consistent manner.

To transform a subjective concept into one amenable to aggregation with other quantitative data, the function WEIGHT, mentioned above, is used. At the lowest level the user is presented with a list of categories to describe each input. For example, if we take the Management Character branch of the tree, the user must perform two evaluations: Commitment and Integrity. For Commitment the user must choose an evaluation of VERY-HIGH, HIGH, AVERAGE, LOW and VERY-LOW and for Integrity the user has options of QUESTIONABLE, ACCEPTABLE and OUTSTANDING.

To evaluate these two inputs and form an assessment of Management Character MRA uses two weight rules in which the votes are chosen specifically to ensure the assessments match the experts' views. The first weight rule specifies the impact of Commitment on Management Character. The table below specifies this weight rule:

User's Answer	Votes
VERY-HIGH	24
HIGH	12
AVERAGE	0
LOW	-12
VERY-LOW	-24

Table 3. MRA weight rules (user's answers a)

The second weight rule specifies the impact of Integrity:

User's Answer	Votes
OUTSTANDING	20
ACCEPTABLE	0
QUESTIONABLE	-150

Table 4. MRA weight rules (user's answers b)

2.9 Statistical models

A common alternative modelling scheme for credit analysis is the use of statistical models of various sorts. These models can be potentially very powerful for predicting default and are often optimized to do this specifically. For this comparison, we consider only the state of the art in statistical models to rationalize our comparisons.

Statistical models are typically designed to predict default or to predict agency ratings. The most sophisticated of these take advantage of modeling techniques that control for data problems and non-linearity as well as the complexity of interactions. Nonetheless, most statistical models often deal poorly with missing data. Although well designed quantitative models can provide a level of explanatory functionality for their outputs in the form of driving factors, marginal effects, etc. for the input variables, they do not typically give deep insight into the credit process through these tools.

Most quantitative models are derived through statistical optimization and are thus not amenable to ad-hoc adjustment. Rather, this needs to be done by re-optimising the model using new data. The compact formulaic representation of statistical models makes them ideal for embedding in other systems and they are computationally efficient which gives them very fast response speed.

The biggest advantage to using a high quality statistical model is the accuracy of its predictions which is typically high compared to alternatives (including expert systems). Also, the objective nature of statistical models makes them well suited to use as benchmarks for transactions between firms.

Attribute	Ideal Solution	STAT	MEETS
Accuracy	HIGH	HIGH	✓✓
Explainability	HIGH	MODERATE	
Tolerance for noisy data	MODERATE	MODERATE	✓
Tolerance for sparse data	MODERATE	LOW	
Tolerance for complexity	HIGH	MOD - HIGH	✓
Response Speed	MODERATE	HIGH	✓✓
Flexibility	HIGH	LOW	
Embedability	MODERATE	HIGH	✓✓

Table 5. Statistical Models

2.10 Scorecard models

Like statistical models, scorecard models provide a framework based on the assessment of a small number of financial ratios. The mathematical model used for scorecard construction is typically parameterized either based on expert judgement or statistically. Like some statistical models, these models are often constrained to consider (additively) a small number of factors without interactions.

Scorecards have been very successful in high volume domains (consumer lending, revolving consumer credit, etc.) where there is a significant number of data records on borrowers; a large degree of uncertainty in the predictability of default; it is often difficult do get detailed information on a borrower; and a few indicators can provide sufficient information on the likelihood of default. Scorecards also often take advantage of behavioral information such has payment histories, etc. The main distinction between scorecards and more involved statistical models is one of accuracy and sophistication.

Typically, scorecard models require the user to provide a series of inputs. Each input is assigned a value and these are summed to result in a score. The institution uses the score to help determine whether to lend to the borrower.

Attribute	Ideal Solution	SC	MEETS
Accuracy	HIGH	MODERATE-HIGH	~✓
Explainability	HIGH	LOW	
Tolerance for noisy data	MODERATE	LOW	
Tolerance for sparse data	MODERATE	LOW	
Tolerance for complexity	HIGH	MODERATE	
Response Speed	MODERATE	HIGH	✓✓
Flexibility	HIGH	LOW	
Embedability	MODERATE	HIGH	✓✓

Table 6. Scorecard Models

2.11 Comparing Statistical, Scorecard and MRA models

In reviewing the above analysis, summarized in the table below, some clear patterns emerge. As we’ve defined the underwriting problem, MRA is clearly the favored of the three approaches. Its major weakness is its relatively slow response speed. This is more a function of the time required to input the necessary data than of the computation time. However, the reward for undertaking this detailed data gathering effort is that it provides much deeper insight into the drivers of credit than other approaches and allows much more flexibility for organizations to shape it to reflect their internal standards and credit culture.

We note, however, that there are other credit applications for which the other techniques might be a better fit than MRA. Interestingly, using our analysis of the underwriting problem, we can also draw conclusions about the other two approaches. If quick, objective, high precision default prediction is the primary goal then other techniques cannot compete with statistical models, which clearly distinguish themselves.

This is often the requirement for:
• trading
• securitization

• portfolio management
• screening and monitoring

On the other hand, if complex modeling is not required, but flexibility, simplicity and speed matters, scorecard approaches suggest themselves. These are often the requirements for higher volume, lower exposure underwriting applications.

Attribute	Ideal Solution	MRA	STAT	SC
Accuracy	HIGH	✓	✓✓	~✓
Explainability	HIGH	✓		
Tolerance for noisy data	MODERATE	✓	✓	
Tolerance for sparse data	MODERATE	✓		
Tolerance for complexity	HIGH	✓	✓	
Response Speed	MODERATE		✓✓	✓✓
Flexibility	HIGH	✓		✓
Embedability	HIGH	✓	✓✓	✓✓

Table 7. Statistical, Scorecard and MRA

We have described in detail an expert system-based approach to solving this decision support problem called Moody's Risk Advisor. MRA has been in use in large financial institutions for many years. The system is implemented in a proprietary expert systems language called Syntel™. The language provides representational ability rich enough to perform both numerical and subjective analyses and powerful enough to combine these into composite assessments for the analyst.

MRA allows an analyst to represent business expertise in a manner with which they are familiar using standard business concepts combined and weighted together using expert judgment. The system treats uncertainty in a consistent manner. It can present its evaluations in a form that shows graphically both its assessment and the uncertainty associated with it. MRA also provides support for handling incomplete information and thus can still perform analyses when some information is unavailable.

Explanation reports provide a drill-down analysis of a particular case by combining naturallanguage commentary with a more detailed view of sub-assessments than can be shown in the screens.

MRA also provides a method for users to override assessments and to document extra information relevant to each field. It also provides a method to warn the user instantly of any considerations he or she should take into account. This feature is valuable in real world deployments since credit committees are often interested in features of a borrower that are unusual and may not be captured in the standard knowledge base.

Importantly, MRA allows experts within an organization to modify the knowledge base, thus permitting the system to more closely conform with and support the internal credit culture and best practices of the firm. It is equally important to note, however, that this flexibility generally precludes the outputs of the system from being used outside the organization. The very attributes that allow extensive customization of the knowledge base for specific credit environments prevent two organizations from being able to objectively use the measure as a basis for transactions since they cannot use the (differently) customized systems as a common basis for comparison.

We compared this approach with two other common ones in this domain. Based on our analysis of the underwriting domain, the knowledge-based system was favored. Overall the utility of this knowledge base technology has been borne out in practice. It has demonstrated itself to be well suited to support the credit underwriting process. In particular, by affording the ability to describe knowledge in a natural manner it provides a representation sufficient to model credit expertise, yet intuitive enough for bankers and credit professionals to understand and modify it. The flexibility of MRA allows it to be tailored to become an integral part of an institution's lending procedures and this has in fact been the observed outcome in a number of large financial firms.

2.12 Limitations of Credit Risk Advisors

From the aforementioned analysis of the credit risk advisors’ models, we should mention and highlight the following:

- Although **the aforementioned models offer the best view for the client, they cannot offer clear indications for the debtors**. More specifically, in the most common scenario, debtors are SMEs that do not have published balance sheets and offer a few economic indicators that are revised in a yearly period, ignoring that the factoring company’s lending horizon is 30 to 90 days.

- Moreover, from the analysis made in the previous section, it appears that MRA offers a precise representation of the credit status of a firm. MRA results are based on the data stored in its database. The data used by MRA can be characterised as static, as they are not updated often**. More specifically MRA data, used for the credit risk assessment of large corporate businesses, are updated on a yearly basis, and are based on yearly published balance sheets. It appears, that this is a really important limitation of MRA, especially when used in factoring. This happens because in factoring the period of recycling credit is one to three months.**

- **In addition, we should mention that the presented models are generally used by financial institutions and are not specific on factoring.**

Therefore, from the aforementioned findings and analysis it appears that living in a very volatile economic environment we would pay more attention to have a revising aspect even by week or month for the debtors of our client, especially, if we take risk on them.

CHAPTER 3

CONCEPTUAL MODEL

CHAPTER 3: CONCEPTUAL MODEL

Summary

In this chapter we identify, present and analyse the indicators that must be considered to assess default risk in non-recourse factoring. These indicators, measured typically at successive times (time series), produce the IoD formula for each debtor. After this, deriving the expected revenue formula, factor may decide if continue to funding this client's debtor. Using this methodology, we rate specific financial indicators, in time series, assessing the default risk in a non-recourse factoring, taking in parallel funding decisions.

3.1 Conceptual Model Development

Based on the issues presented in the previous chapter, we will try in the third chapter to identify and propose a model that will support the measurement of default risk in non-recourse factoring. In identifying the conceptual model, we will follow these steps:

Step 1. Identify and present the main categories of the indicators that support the measurement of default risk in non-recourse factoring.

Step 2. Identify and analyse the actual indicators falling in each category.

Step 3. Justify and propose the matrix and formula that the factoring companies will have to use to measure with the predefined indictors the default risk in non-recourse factoring.

Step 4. Identify and describe the guidelines that the factoring companies will have to use after measuring default risk into decision making process.

In the following sections the aforementioned steps will be analysed.

Step 1. Identify and present the main categories of the indicators that support the measurement of probability of default in non-recourse factoring.

In doing so, initially we propose that the indicators that support the measurement of probability of default in non-recourse factoring fall in two main categories, namely: (a) derogatory and (b) financial. These main categories of the indicators are described in the following paragraphs:

- **Derogatory indicators** are of high importance in non-recourse factoring. As it has been already mentioned, risk is taken over each debtor. So, we should reveal these indicators that in best way reflect the derogatory behaviour of the debtor, as well as its ability to pay obligations in time.

- **Financial indicators** constitute the second category. It is evident that we must pay attention to information offered, which reflects the financial obligations of the debtor not only to our client, but also to all financial institutions. In doing so, we have in current time a clear aspect for debtor's cash management, and we can more easily predict future defaults.

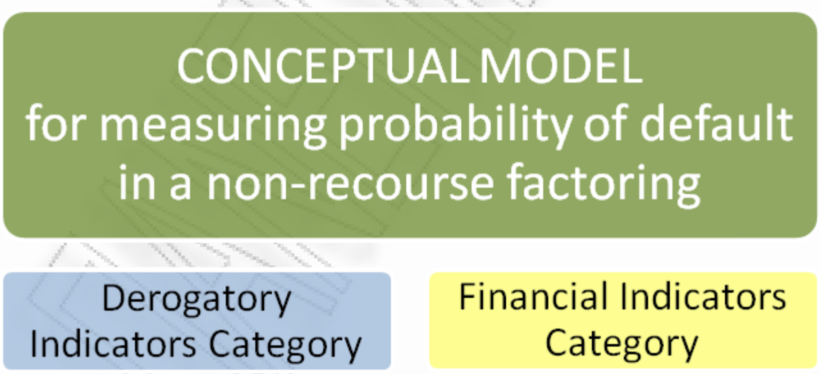

Diagram 1. Main categories of the indicators (Step 1)

Based on Bank of Greece Governor's Acts 2442/29-1-1999, 2513/15-1-2003, 2565/11-10-2005, 2589/20-8-2007, any financial institution should make previsions, for any claim or credit is not been paid at the time arranged. These previsions are divided to the following categories:

1. 0 - 90 days,
2. 90 – 180 days,
3. 180 – 365 days,
4. 365 plus days.

Making the adoption to a factoring company’s portfolio, we highlight that factoring is not a common loan, as it has been clear from the aforementioned analysis. It is evident that when we try to measure default risk in non-recourse factoring, we should focus to delays of each debtor, and not to the sum of delays of clients’ portfolio as a whole.

Step 2. Identify and analyse the actual indicators falling in each category.

After identifying and presenting the categories that our conceptual model should consist of, the next step is the identification and justification of the indicators that these categories comprise of.

In the **derogatory indicators category**, we propose that the following indicators should be included:

1. **Delay in € (90 days) / open invoices**

This indicator is the first evidence of delay over the period of payment and constitutes the sign of extra care. We should attend, if this phenomenon is transitory or monitor the first financial faults of the debtor. The early detection of delays in factoring gives factor the opportunity not to fund other invoices and consequently protect from exposure to risk

2. **Delay in € (90-180 days) / open invoices**

The second indicator gives a sign of financial disorder. It may happens when period of credit is enlarged than usual up to 270 days. It is evident that we may affront situations that invoices will be unpaid for more than 90 days. The legal department must be about for actions which will protect factor’s interests.

3. **Delay in € (180+ days) / open invoices**

This indicator shows that legal actions are inevitable. Factor faces greater default risk for the invoice funded and whose delay of payment is more than 180 days.

4. **Period of credit (in days)**

This indicator reflects the cash flows of the debtor. Even if we are within the arranged credit period, debtor may be willing to reduce this period to succeed a better commercial agreement. This would reflect a rather reduced default risk.

The aforementioned indicators (1-4) refer to derogatory behaviour of each debtor to the client and represent mainly derogatory information and reveal in current time the financial position of the debtors. As in non-recourse factoring, we take risk on debtors, we have to know in any time how they meet our financial standards. These indicators may change even by day, but we will **rate them on a monthly basis.**

In the **financial indicators category**, we propose that the following indicators should be included**:**

5. **Default Financial Obligations System**

The Default Financial Obligation System contains data (e.g. bounced checks, liquidation auction announcements, bankruptcies) concerning the credit behavior of individuals and companies. Both DFO & MPS aim at supporting a more accurate assessment of the financial credibility of the clients (current or future) by the banks.

6. Credit Consolidation System

Credit Consolidation System contains data concerning consumer and housing loans, credit cards of natural persons and credit to small and medium-size businesses. It contains information about the status of the credit (current balance with no delinquency, deliquent balance etc). The function of the Databank and all the relevant activities secure the regular collection of data from credit/financial institutions regarding possible debts from loans, their processing, the completeness control as well as the dissemination of the processed information.

Indicators **5** and **6** show the immediate financial condition of each debtor as it is processed on the database of **Tiresias**. **Tiresias** is an inter banking company which processes data that reflect the economic behavior of individuals and companies as well as data that contribute to the prevention of fraud in financial transactions. The distributed data contribute to the protection of credit, the reduction of credit risk and the improvement of financial transactions, to the benefit of individuals and the banking system in general.

The categories of indicators as well as the indicators that our model consists of are displayed in the following diagram.

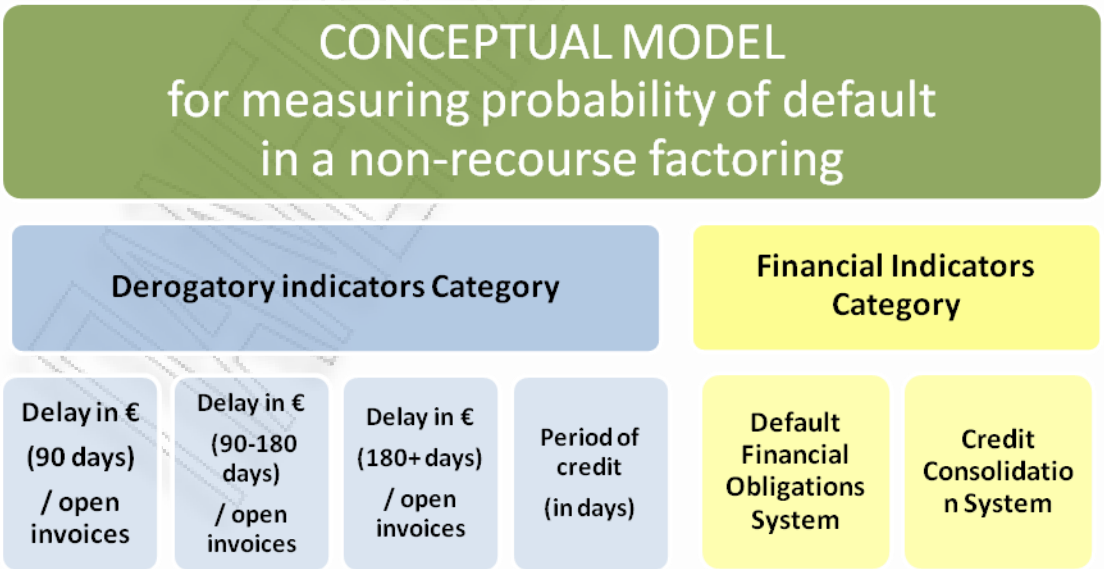

Diagram 2. Main categories and indicators (Step 2)

Step 3. Justify and propose the matrix and formula that the factoring companies will have to use to measure with the predefined indictors the default risk in non-recourse factoring.

In this step, the author justifies and proposes a matrix and formula that the factoring companies will have to use to measure with the predefined indictors the default risk in non-recourse factoring.

In doing so, we will create our table, using the data that we have gathered from the factoring company. This table includes values for the aforementioned indicators for each client's debtor (APPENDIX I). This procedure is repeated for twelve months data for each client's debtor.

This table will be consisted of the aforementioned indicators and each debtor. The name of the table will represent each client. In other words the table will have M rows and N columns (MxN).

M rows, one for each debtor,

N columns, (6) as the number of indicators.

In this step, we are about to derive a new formula for default risk, this of Indicator of Default (IoD), using the aforementioned indicators. This formula reflects in any time defaults that concern not only the factoring company, but also reveal the holistic derogatory behaviour of the debtor. So, the **novel formula proposed** is the following:

$$IoD = W1 \times IND1 + W2 \times IND2 + W3 \times IND3 + W4 \times (IND5 \div IND6)$$

To estimate Wi, we regress the collected data.

As a result, we can estimate IoD.

Step 4. Identify and describe the guidelines that the factoring companies will have to use after measuring default risk into decision making process.

By the result of the estimation of IoD, the factor should take the decision to continue financing client for this debtor or not.

To decide whether the financing will continue, the factor has to consider the estimated income of this debtor over the period of credit. In other words, we now have to define the formula of expected revenues, after considering IoD. So, the novel formula proposed, is the following:

$$E(r) = (1 - IoD) \times X_{II} \div (1 + R \div 12)^{(IND4 \div 30)}$$

And moreover the formula of funding over a period that coincides with period of credit is:

$$F = a \times X_{ii}$$

where

a – funding ratio,

Xii – funding amount,

If E(r) < F, the factor decides not to fund any more this client’s debtor, for a lending horizon which coincides with the period of credit (IND4).

Using the aforementioned formula and guidelines, we will have the default risk for a client on a non-recourse factoring, after considering the risk, in unique, for each debtor. Data collection for indicators as well the whole procedure will be repeated on a monthly basis.

CHAPTER 4

RESEARCH METHODOLOGY

Summary

In this section we present the research methodology that acts as the blue print for the research process, and supports the evaluation of the proposed conceptual model related to the estimation of the coefficients of the indicators presented in chapter 3. To do so, we will use EViews which is a statistical package used mainly for time-series oriented econometric analysis. Among other options, we estimate coefficients using Maximum Likelihood - Binary Probit (Quadratic hill climbing) method.

4.1 Introduction

To decide whether the financing will continue, the factor has to consider the estimated income of this debtor over the period of credit. In doing so, the author proposed in Chapter 3, that the factoring companies should do the following:

Estimate IoD, as described in chapter 3, using the following novel formula.

$$IoD = W1 \times IND1 + W2 \times IND2 + W3 \times IND3 + W4 \times (IND5 \div IND6)$$

Estimate E(r), as described in chapter 3, using the following novel formula.

$$E(r) = (1 - IoD) \times X_{II} \div (1 + R \div 12)^{(IND4 \div 30)}$$

In the following paragraphs, estimation methods used, are analysed.

4.2 Estimation methods

There are two generally used methods of estimation: (a) ordinary least squares (OLS) and (b) maximum likelihood (ML). Although OLS method is used extensively in regression analysis, these two methods generally give similar results.

Maximum likelihood estimation is a popular statistical method used for fitting a statistical model to data, and providing estimates for the model's parameters. The method of maximum likelihood corresponds to many well-known estimation methods in statistics. For a fixed set of data and underlying probability model, maximum likelihood picks the values of the model parameters that make the data "more likely" than any other values of the parameters would make them. Maximum likelihood estimation gives a unique and easy way to determine solution in the case of the normal distribution and many other problems, although in very complex problems this may not be the case.

Binary Dependent Variable Models

In this class of models, the dependent variable, may take on only two values— might be a dummy variable representing the occurrence of an event, or a choice between two alternatives. In our case, we are interested in modeling the status of default. (whether default or not). The indicators described in chapter 3 are denoted as X. The goal is to quantify the relationship between the indicators and the probability of default.

Theory

Suppose that a binary dependent variable, Y, takes on values of zero and one. A simple linear regression of Y on X is not appropriate, since among other things, the implied model of the conditional mean places inappropriate restrictions on the residuals of the model. Furthermore, the fitted value of Y from a simple linear regression is not restricted to lie between zero and one.

In statistics and econometrics, a probit model is a popular specification for a binary response model which employs a probit link function. This model is most often estimated using standard maximum likelihood procedure, such estimation is called probit regression. Probit models were introduced by Chester Bliss in 1935, and a fast method for computing maximum likelihood estimates for them was proposed by Ronald Fisher in an appendix to the same article

Our econometric model is a discrete regression model in which the dependent variable Yij is binary, where i=(1,2,3,4,5,6) refers to debtors and j=(1,2,3,4) refers to indicators. We assume there is an underlying response variable Yij* defined by the regression relationship $Y_{ij}{*}=X_{ij}\beta + \varepsilon_{ij}$ where X_{ij} is the vector of the explanatory variables of the i^{th} debtor, ε is the error term (assumed to be standard normal with $\varepsilon i \sim N(0, \sigma^2)$ and β is a vector of coefficients to be estimated. In practice, $Y^{*}ij$ is unobservable. What we observe is the dummy variable Y_{ij} defined by

$Y_{ij} = 0$, if the estimated revenues have collected

$Y_{ij} = 1$, otherwise.

At each month, for each debtor i, Y_i takes the value 1 if the debtor has not paid the estimated claim, and 0 if the debtor has paid the pre-fixed claim. The log-Likelihood Function is given by $\ln(L) = \sum_{i}^{n} [(1 - Y_{ij}) \ln\left(1 - F\left(X_{ij}\beta\right)\right) + Y_{ij} ln(F\left(X_{ij}\beta\right))]$

Because F(·) is strictly between 0 and 1 for probit, $\ln(L)$is well defined for all values of β. A non-linear estimation procedure is used to obtain parameter estimates for the probit specification.

Multicollinearity

Multicollinearity is a statistical phenomenon in which two or more predictor variables in a multiple regression model are highly correlated. In this situation the coefficient estimates may change erratically in response to small changes in the model or the data. Multicollinearity does not reduce the predictive power or reliability of the model as a whole; it only affects calculations regarding individual predictors. That is, a multiple regression model with correlated predictors can indicate how well the entire bundle of predictors predicts the outcome variable, but it may not give valid results about any individual predictor, or about which predictors are redundant with others.

In our case, when we use the maximum likelihood – binary probit method, we face the phenomenon of multicollinearity. That's why, we regress each indicator.

4.3 Empirical Research Methodology

The author has developed an empirical research methodology that acts as the blue print for the research process, to evaluate the proposed conceptual model. The proposed empirical research methodology takes into account the variants discussed and justified in the previous sections. Moreover, this methodology is based on three development stages namely: (a) research design, (b) data collection and (c) data analysis (Jankowicz, 2000).

4.3.1 Research Design

The research design proposed is the first independent part of the empirical research methodology. The starting point is to review the literature, thus developing an understanding of the research that has been done and to identify a suitable void. From the literature review, several issues emerged for a more focused study on default risk on factoring. Miles and Huberman (1994b) mentioned that the latter (formulation of research issues) may precede or follow the development of the conceptual model. From the literature, several research issues were highlighted and identified, so as to support the conceptual development and to make the study on default risk on factoring more focused. This led to a specific research area and identified a research need. Thereafter, a conceptual model that represents the intended empirical research was developed. Based on the needs of the empirical study, it was decided that the research design would employ quantitative research methods (as explained in the previous sections). The data collection was the second step of the proposed empirical research and is analysed in the following Section.

4.3.2 Data Collection

The aim of the second part of the empirical research methodology is the collection of rich set of data surrounding the specific research issue, and the capture of the contextual complexity. Important issues that the author considered are the consistency among data collectors and the accuracy in data recording. A quantitative strategy can offer a 'holistic' view of the processes involved, as well as a realisation of the topic under research. The main and single source of data used to evaluate the conceptual model, came from the real market. More specifically, the author collected real data from a Hellenic factoring company, which is not named for confidentiality reasons. The data used are displayed in Appendix I.

4.3.3 Data Analysis

The final step of the proposed empirical research was the data analysis. At this stage, the author interpreted the data presented in Appendix I. The data analysis supports the interpretation and understanding of the phenomenon under research. The interpretation of quantitative data is a continuous process that begins in the research setting and involves the data collection and validation processes. Thus, the proposed conceptual model was redefined. Moreover, conclusions were drawn and verified and the implications for the research and action were generated.

CHAPTER 5

DATA ANALYSIS

Summary

In this section we present the data, which have been used to estimate coefficients and which will be used to offer funding information in our decision making process. As it has been mentioned, these data come from a Hellenic factoring company which is not named for confidentiality reasons. As we derived the data for each indicator, to reduce **overlap** among indicators, we deducted information that has be calculated to the previous indicator.

5.1 Data Discussion

In Chapter 3, we mentioned that in order to identify the conceptual model, we will follow these steps:

Step 1. Identify and present the main categories of the indicators that support the measurement of default risk in non-recourse factoring.

Step 2. Identify and analyse the actual indicators falling in each category.

Step 3. Justify and propose the matrix and formula that the factoring companies will have to use to measure with the predefined indictors the default risk in non-recourse factoring.

Step 4. Identify and describe the guidelines that the factoring companies will have to use after measuring default risk into decision making process.

At this stage, Step 1 and 2 have already been completed in Chapter 3.

Regarding Step 3, the author initially collected the appropriate data for the indicators identified. The data used to evaluate the proposed model (Appendix I), had been collected by a Hellenic Factoring Company, which is not named for confidentiality reasons. Moreover, the data are observed on a monthly basis. Some of them may change even by day, but it is not a frequent phenomenon. So, we estimate the independent variables which are the indicators on a monthly basis. Previous investigations about factoring are not published, so there is not a similar data collection process published.

One of the most important problems in the process of estimating coefficients was the data overlapping. In our initial data, as they were extracting by the factoring company, what was itemized to be indicator 2, was included in indicator 1, and consequently, what was itemized as indicator 3, was included in indicator 1 and in indicator 2. Non-overlapping data may have auto-correlated errors.

To regress the four indicators that consist the IoD formula, the author used the data collected and tested them using EViews. By the EViews analysis, it appeared that ***when we use the maximum likelihood – binary probit method, we face the phenomenon of multicollinearity.***

Multicollinearity is a statistical phenomenon in which two or more predictor variables in a multiple regression model are highly correlated. In this situation the coefficient estimates may change erratically in response to small changes in the model or the data. Multicollinearity does not reduce the predictive power or reliability of the model as a whole; it only affects calculations regarding individual predictors. That is, a multiple regression model with correlated predictors can indicate how well the entire bundle of predictors predicts the outcome variable, but it may not give valid results about any individual predictor, or about which predictors are redundant with others.

Therefore, we regress each indicator separately using EViews. The results are displayed below.

RESULTS FOR INDICATOR 1

Dependent Variable: Y
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 12/04/09 Time: 17:23
Sample: 1 72
Included observations: 72
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.789044	0.375347	-4.766369	0.0000
IND1	**30.16261**	6.138438	4.913728	0.0000

Mean dependent var	0.444444	S.D. dependent var	0.500391
S.E. of regression	0.344027	Akaike info criterion	0.726927
Sum squared resid	8.284802	Schwarz criterion	0.790168
Log likelihood	-24.16938	Hannan-Quinn criter.	0.752104
Restr. log likelihood	-49.46123	Avg. log likelihood	-0.335686
LR statistic (1 df)	50.58371	McFadden R-squared	0.511347
Probability(LR stat)	1.14E-12		

Obs with Dep=0	40	Total obs	72
Obs with Dep=1	32		

RESULTS FOR INDICATOR 2

Dependent Variable: Y
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 12/04/09 Time: 17:25
Sample: 1 72
Included observations: 72
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.677084	0.193488	-3.499363	0.0005
IND2	**64.73742**	19.84987	3.261353	0.0011

Mean dependent var	0.444444	S.D. dependent var	0.500391
S.E. of regression	0.407353	Akaike info criterion	1.017272
Sum squared resid	11.61558	Schwarz criterion	1.080513
Log likelihood	-34.62180	Hannan-Quinn criter.	1.042449
Restr. log likelihood	-49.46123	Avg. log likelihood	-0.480858
LR statistic (1 df)	29.67886	McFadden R-squared	0.300021
Probability(LR stat)	5.10E-08		
Obs with Dep=0	40	Total obs	72
Obs with Dep=1	32		

RESULTS FOR INDICATOR 3

The results for indicator 3 show no statistical importance.

RESULTS FOR INDICATOR 4

Dependent Variable: Y
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 12/04/09 Time: 17:26
Sample: 1 72
Included observations: 72
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.420500	0.184329	-2.281246	0.0225
IND4	**6.901092**	2.747675	2.511612	0.0120

Mean dependent var	0.444444	S.D. dependent var	0.500391
S.E. of regression	0.480664	Akaike info criterion	1.330446
Sum squared resid	16.17268	Schwarz criterion	1.393687
Log likelihood	-45.89605	Hannan-Quinn criter.	1.355622
Restr. log likelihood	-49.46123	Avg. log likelihood	-0.637445
LR statistic (1 df)	7.130360	McFadden R-squared	0.072080
Probability(LR stat)	0.007579		

As it has been made clear from the aforementioned analysis, because of data overlapping and multicollinearity we regress each indicator separately. Applying results of estimation in IoD formula it is transformed as following:

$$IoD = 0,301 \times IND1 + 0,647 \times IND2 + 0,069 \times (IND5 \div IND6)$$

In **Step 4**, we apply IoD results into Expecting Revenues formula

$$E(r) = (1 - IoD) \times X_{II} \div (1 + R \div 12)^{(IND4 \div 30)}$$

The results are displayed in Appendix II.

Then we calculate the funding amount by using the following formula (as explained in Chapter 3)

$$F = a \times X_{ii}$$

Where: a – funding ratio and Xii – funding amount.

The results are displayed in Appendix II.

If the expected revenues are under the funding amount, it reflects an exceeding funding amount done over the risk taken.

Calculating the monthly exceeding funding for each debtor we find an annual average of 10,2% over the amount that is admitted by the risk taken over this contract. <u>The most important finding is the direct information of the derogatory and financial statement of each debtor.</u> This set of information must not be underestimated because may lead to crucial decisions such as: (a) break of the whole contract, (b) stop funding of a precise debtor, (c) revision of contracts' terms such as rate, period of credit or funding ratio.

CHAPTER 6

CONCLUSIONS AND FURTHER RESEARCH

Summary

This chapter concludes the research reported in this dissertation, presents its novelty and contribution, and proposes areas of further work. Chapter 6 begins by summarising the dissertation and drawing conclusions that derived from both the literature and empirical research reported in this dissertation. The limitations of the research undertaken are identified and presented, and the author proposes that these limitations should be considered when interpreting results. Thereafter, a critical evaluation of the research process is presented. The novelty claimed in this dissertation is then summarised. Finally, this last chapter concludes with the identification and discussion of further research directions, in this challenging and fast-evolving research area of factoring including the associated risks.

6.1 Research Overview

In Chapter 2, the author reviewed the normative literature and presented the institution of factoring such as its advantages and disadvantages. Moreover, MRA model of credit assessment as well ICAP's approach have been analysed. Then, the author revealed the gap existing today in measuring risk in a non-recourse factoring.

Thus, to extend the established norms and to overcome the limitations existing methods, in Chapter 3, we proposed a debtor oriented approach in measuring risk. To better understand the nature of non-recourse factoring, it was suggested that the debtors of a client should be classified and identified. That's why, we established a new term, this of Indicator of Default (IoD), which consists of four indicators. Using IoD, we receive the maximum set of information about the derogatory behaviour of each debtor. This reflects its cash flow statement, considering that the most business in Greece are SME without published balance sheets. Using the IoD as well the formulas of expecting revenues and the funding amount, we defined our conceptual model.

Chapter 4 justifies the selected research methodology used in this dissertation. A quantitative research methodology has been adopted. Moreover, we have used EViews statistical package to estimate indicators' coefficients described in chapter 3.

In chapter 5, empirical data are selected and analysed. These data come from a Hellenic factoring company which is not named for confidentiality reasons. Moreover, the preliminary research findings, the data retrieved to explore the conceptual model and the issues under investigation were described.

Thereafter, Chapter 6 used the empirical data to: (a) provide the lessons learnt from this research and (b) draw conclusions based on the aforementioned procedure. The empirical findings confirmed the need to adopt another risk measuring process in non-recourse factoring. Such a process can be used by the factoring organisations as a decision-making tool taking funding decisions. It is not claimed that the proposed model is appropriate for all decision-making situations; however, it can establish itself as being a novel and beneficial approach to support factoring.

6.2 Meeting the Objectives of this Dissertation

In order to achieve the aim of this dissertation, a number of objectives were defined in Chapter 1 and have been accomplished as discussed in the previous chapters. These objectives are summarised in Table 8 and analysed in the following paragraphs.

Objective	**Section/Chapter**
Objective 1	Chapter 1 and Chapter 2
Objective 2	Chapter 2 and Chapter 3
Objective 3	Chapter 4
Objective 4	Chapter 4 and Chapter 5
Objective 5	Chapter 6

Table 8: Meeting the Objectives of this Dissertation

Objective 1: Present and analyse the normative literature related to factoring and more specifically to non-recourse factoring.

Based on the literature review, a number of research gaps had been identified and had been further examined and investigated by the researcher (met in Chapter 1 and Chapter 2).

Objective 2: Propose a novel model for default risk in non-recourse factoring.

Based on the literature review, limited research has been conducted in the area of default risk in factoring organisations, with the majority of this research focusing on factoring as mean of funding. Our research highlights a new approach of measuring risk to this crucial institution of funding.

Objective 3: Present the research methodology.

To overcome the limitations of credit risk model, Chapter 3 proposed that IoD should give another approach to risk measurement. To better understand risk in non-recourse factoring, it is proposed that they should be classified and identified on each debtor. In doing so, the author conceptualised a structured method to support factoring companies into making decisions towards funding.

Objective 4: Evaluate and enhance the proposed model.

To test the proposed model, an appropriate research methodology was justified and explained in Chapter 4. Thereafter, Chapter 5 presented and analysed the empirical data collected from a Hellenic factoring company.

Objective 5: To extrapolate conclusions and provide a novel contribution to the domain of default risk in non-recourse factoring.

In Chapter 6, the research findings derived from data processing were considered and discussed. These findings support decision-makers of factoring. Moreover, Chapter 6 begins by summarising the dissertation and drawing conclusions that derived from both the literature and empirical research reported in this dissertation. In addition to this the novel contribution is stated.

The accomplishment of the above objectives has been made possible through the development of a ***novel conceptual model for the examination of issues related to***

default risk in non-recourse factoring. This was demonstrated by examining the limitations of the established risk measurement and addressing a new approach in factoring organisations. Thus, this research has ***contributed to both theory and practice.*** The individual elements of the contribution made by this work stem from different components in this dissertation: from the contextual information provided in Chapters 1, 2 and 3, to the research methodology reported in Chapter 4, through the design and the conduct of the data reported in Chapter 5, and finally, the empirical analysis of the findings and the discussion of conclusions presented in Chapter 6.

6.3 Main Findings

The main findings derived from the work presented in this dissertation are presented below:

Finding 1	By reviewing the normative literature, the author suggested that non-recourse factoring needs another approach to measure default risk, as risk is undertaken over each debtor separately.
Finding 2	The author reviews the normative literature and reveals that credit risk models are inadequate to measure default risk, as more businesses in Greece are SME and do not dispose published balance sheets. Additionally, the factor of "time" pushes to more flexible and fast techniques of measurement default risk.
Finding 3	The literature review indicated that there is limited research in the area of factoring and the measurement of associated risks.
Finding 4	IoD method not only gives a direct and reliable derogatory statement of each debtor, but also used in the defined as expected revenue formula may be a decision making tool.
Finding 5	Applying the IoD method in the data set, we identified the exceeding funding amount that the factoring company should not fund the precise debtor.

Finding 6 From the empirical data and the theoretical analysis, the issues proposed for further research and the conceptual model were examined and validated.

6.4 Statement of Contribution and Research Novelty

The individual elements of the contributions made by this work stem from different components in this dissertation. From the contextual information provided in Chapters 1, 2 and 3, to the research methodology reported in Chapter 4, through the data set reported in Chapter 5 and finally the empirical analysis of the findings as well conclusions presented in Chapter 6. The work presented in this dissertation has made novel contribution to the area of factoring and more specifically to the measurement of default risk and has extended the boundaries of knowledge.

The author claims that this research has novel contribution in the following three main areas: (a) Novel approach of risk measurement in non-recourse factoring, (b) Novel Model for IoD and (c) Novel Method for Expected Revenues. Table 9 summarises the research novelty and contribution of this dissertation.

		Research Novelty	Research Contribution
Novel Interpretation of Normative Literature	Novel approach of risk measurement	✓	✓
	Presentation of the particularity of non-recourse factoring	✓	✓
Novel Model for IoD	Definition of six indicators	✓	✓
	Novel definition of Indicator of Default (IoD)	✓	✓
Novel Method for Expected Revenues	Novel combination of IoD into the formula of Expecting Revenues	✓	✓

Table 9: Research Novelty and Contribution

6.5 Research Limitations

As described and justified in Chapter 4, to collect and interpret the data, a quantitative method was used. This method has been proved to provide significant benefits, as it allows to have a countable result of our approach. However, this research method has some limitations, with a number being encountered in this research. Initially, the collection and analysis of quantitative data has proved time consuming and demanding. Moreover, the confidentiality of the factoring institution can be considered as a limitation. The most important limitation seems to be the lack of an information system, which could be used in a common basis of factoring companies to produce the data for indicators defined in chapter 3.

In addition, the relationship between theory and research might be considered weak and unstructured, as quantitative approaches may be criticised for not instilling theoretical elements. However, in the case of this research, the author sought to partially address this concern through developing a conceptual model that incorporates influential factors, combining them with specific weights to derive IoD model. This model consisted of indicators not defined in previous research.

Finally, there is much concern regarding the extent that quantitative research can be generalised beyond the confines of the inquiry, as the sample of companies in factoring are often relatively few. However, the methodology presented in Chapter 4 was developed as it was considered safer to identify and investigate independent variables following a review of literature. Having now evaluated the research process, such concern needed not of been considered important, as this approach may also have been suitable, and yet, still provided 'freedom' and scope for: (a) discovery and theory building and, (b) discovery, theory building and testing.

The main difficulty the researcher faced was the restricted access to information, such as clients' documents, which was due to confidentiality reasons. Finally, the researcher failed to arrange appointments with some top executives, since they had demanding schedules.

6.6 Avenues for Further Research

- It seems to be more logical, as we move from indicator 1 to indicator 2 and indicator 3, coefficients take a higher value. Maybe another method of estimation should be more suitable.
- Another issue for further research should be the correlation of indicators 1,2 and 3 with indicator 6. Larger sample should give interesting results.
- What is the predictive power of IoD?
- If estimating default risk in non-recourse factoring, what would be hedging techniques?
- The measurement of IoD of a large sample would give a better set of information to explain market risk.
- Another issue that should be investigated is this of pricing with different rate and offers a different period of credit to each client’s debtor basing on IoD results.
- What is the correlation of many IoD indicators with the volume of open invoices and bounced checks in a market?
- Finally, what could offer factoring as public intervention of supporting liquidity with a security system comparing incomes of added taxes to interest expenses?

APPENDICES

APPENDIX I

		IND1	IND2	IND3	IND5/IND6
JAN	D1	0,013	0	0	0,000
JAN	D2	0,170	0	0	0,000
JAN	D3	0	0	0	0,000
JAN	D4	0,039	0,026	0	0,061
JAN	D5	0	0	0	0,000
JAN	D6	0,088	0,019	0	0,163
FEB	D1	0,013	0	0	0,000
FEB	D2	0,196	0	0	0,000
FEB	D3	0	0	0	0,000
FEB	D4	0,046	0,020	0	0,037
FEB	D5	0,012	0	0	0,000
FEB	D6	0,170	0,056	0,011	0,217
MAR	D1	0,007	0	0	0,000
MAR	D2	0,134	0	0	0,000
MAR	D3	0,000	0	0	0,029
MAR	D4	0,046	0,019	0	0,037
MAR	D5	0,000	0	0	0,000
MAR	D6	0,135	0,054	0	0,175
APR	D1	0,012	0	0	0,067
APR	D2	0,114	0	0	0,000
APR	D3	0,026	0	0	0,029
APR	D4	0,042	0,027	0,008	0,037
APR	D5	0,018	0	0	0,000
APR	D6	0,110	0,078	0,004	0,175
MAY	D1	0	0	0	0,066
MAY	D2	0,164	0	0	0,000
MAY	D3	0,024	0	0	0,029
MAY	D4	0,045	0,029	0	0,061
MAY	D5	0	0	0	0,024
MAY	D6	0,128	0,047	0	0,198
JUN	D1	0,033	0	0	0,065
JUN	D2	0	0	0	0,000
JUN	D3	0,056	0	0	0,029
JUN	D4	0,043	0,007	0	0,000
JUN	D5	0	0	0	0,024
JUN	D6	0,134	0,049	0	0,140
JUL	D1	0	0	0	0,063

JUL	D2	0	0	0	0,000
JUL	D3	0,029	0	0	0,077
JUL	D4	0,033	0	0	0,090
JUL	D5	0	0	0	0,024
JUL	D6	0,140	0,052	0	0,000
AUG	D1	0,062	0	0	0,000
AUG	D2	0	0	0	0,000
AUG	D3	0,082	0	0	0,077
AUG	D4	0	0	0	0,090
AUG	D5	0	0	0	0,000
AUG	D6	0,106	0,086	0	0,163
SEP	D1	0,097	0	0	0,000
SEP	D2	0	0	0	0,000
SEP	D3	0,124	0	0	0,000
SEP	D4	0,036	0,010	0	0,077
SEP	D5	0	0	0	0,000
SEP	D6	0,080	0,100	0	0,000
OCT	D1	0,090	0,015	0	0,000
OCT	D2	0,114	0	0	0,000
OCT	D3	0,129	0,029	0	0,072
OCT	D4	0,044	0,017	0	0,000
OCT	D5	0,021	0	0	0,000
OCT	D6	0,077	0,085	0	0,163
NOV	D1	0,090	0	0	0,000
NOV	D2	0,090	0	0	0,000
NOV	D3	0,132	0,006	0	0,046
NOV	D4	0,046	0,005	0	0,000
NOV	D5	0,009	0	0	0,000
NOV	D6	0,059	0,057	0,015	0,199
DEC	D1	0,068	0	0	0,000
DEC	D2	0,054	0	0	0,000
DEC	D3	0,152	0,015	0	0,046
DEC	D4	0,044	0	0	0,000
DEC	D5	0,005	0	0	0,000
DEC	D6	0,062	0,054	0	0,199

APPENDIX II

		IND1	IND2	IND3	IND5/IND6	IoD	E(r)	F	VALUE	EXCEED	RATIO
JAN	D1	0,013	0	0	0,000	0,004	96.386	90.000	YES	0	
JAN	D2	0,170	0	0	0,000	0,051	14.614	14.294	YES	0	
JAN	D3	0	0	0	0,000	0,000	179.014	166.500	YES	0	
JAN	D4	0,039	0,026	0	0,061	0,071	306.386	294.300	YES	0	
JAN	D5	0	0	0	0,000	0,000	476.649	445.277	YES	0	
JAN	D6	0,088	0,019	0	0,163	0,151	116.292	114.611	YES	0	**0,00%**
FEB	D1	0,013	0	0	0,000	0,004	108.211	101.042	YES	0	
FEB	D2	0,196	0	0	0,000	0,059	12.553	12.380	YES	0	
FEB	D3	0	0	0	0,000	0,000	169.338	157.500	YES	0	
FEB	D4	0,046	0,020	0	0,037	0,052	307.473	294.300	YES	0	
FEB	D5	0,012	0	0	0,000	0,004	447.270	419.347	YES	0	
FEB	D6	0,170	0,056	0,011	0,217	0,237	99.913	104.210	**NO**	104.210	**9,57%**
MAR	D1	0,007	0	0	0,000	0,002	105.360	98.202	YES	0	
MAR	D2	0,134	0	0	0,000	0,040	13.867	13.410	YES	0	
MAR	D3	0,000	0	0	0,029	0,000	159.342	148.500	YES	0	
MAR	D4	0,046	0,019	0	0,037	0,026	325.454	311.303	YES	0	
MAR	D5	0,000	0	0	0,000	0,000	413.026	385.842	YES	0	
MAR	D6	0,135	0,054	0	0,175	0,076	106.561	109.350	**NO**	109.350	**10,25%**
APR	D1	0,012	0	0	0,067	0,050	116.217	108.990	YES	0	
APR	D2	0,114	0	0	0,000	0,034	14.759	14.184	YES	0	
APR	D3	0,026	0	0	0,029	0,028	164.799	154.800	YES	0	
APR	D4	0,042	0,027	0,008	0,037	0,056	318.607	306.005	YES	0	
APR	D5	0,018	0	0	0,000	0,005	413.689	388.566	YES	0	

APR	D6	0,110	0,078	0,004	0,175	0,204	105.626	109.350	**NO**	109.350	**10,11%**
MAY	D1	0	0	0	0,066	0,046	121.079	113.130	YES	0	
MAY	D2	0,164	0	0	0,000	0,049	15.400	15.035	YES	0	
MAY	D3	0,024	0	0	0,029	0,027	162.982	153.000	YES	0	
MAY	D4	0,045	0,029	0	0,061	0,074	295.259	284.715	YES	0	
MAY	D5	0	0	0	0,024	0,017	433.403	405.549	YES	0	
MAY	D6	0,128	0,047	0	0,198	0,206	113.324	115.650	**NO**	115.650	**10,64%**
JUN	D1	0,033	0	0	0,065	0,055	124.648	117.630	YES	0	
JUN	D2	0	0	0	0,000	0,000	14.837	13.770	YES	0	
JUN	D3	0,056	0	0	0,029	0,037	169.942	161.100	YES	0	
JUN	D4	0,043	0,007	0	0,000	0,017	290.521	274.716	YES	0	
JUN	D5	0	0	0	0,024	0,017	404.539	378.540	YES	0	
JUN	D6	0,134	0,049	0	0,140	0,169	108.139	110.250	**NO**	110.250	**10,44%**
JUL	D1	0	0	0	0,063	0,043	158.212	148.770	YES	0	
JUL	D2	0	0	0	0,000	0,000	13.674	12.690	YES	0	
JUL	D3	0,029	0	0	0,077	0,062	165.279	156.600	YES	0	
JUL	D4	0,033	0	0	0,090	0,072	275.814	261.315	YES	0	
JUL	D5	0	0	0	0,024	0,017	385.101	360.351	YES	0	
JUL	D6	0,140	0,052	0	0,000	0,076	103.504	104.850	**NO**	104.850	**10,04%**
AUG	D1	0,062	0	0	0,000	0,019	190.842	182.070	YES	0	
AUG	D2	0	0	0	0,000	0,000	13.674	12.690	YES	0	
AUG	D3	0,082	0	0	0,077	0,078	171.950	165.600	YES	0	
AUG	D4	0	0	0	0,090	0,062	269.004	252.315	YES	0	
AUG	D5	0	0	0	0,000	0,000	366.770	342.630	YES	0	
AUG	D6	0,106	0,086	0	0,163	0,200	100.927	104.850	**NO**	104.850	**9,89%**
SEP	D1	0,097	0	0	0,000	0,029	168.215	162.225	YES	0	
SEP	D2	0	0	0	0,000	0,000	15.807	14.670	YES	0	

SEP	D3	0,124	0	0	0,000	0,090	163.253	159.300	YES	0	
SEP	D4	0,036	0,010	0	0,077	0,017	256.512	243.315	YES	0	
SEP	D5	0	0	0	0,000	0,000	337.328	315.126	YES	0	
SEP	D6	0,080	0,100	0	0,000	0,089	113.436	116.550	**NO**	116.550	**11,53%**
OCT	D1	0,090	0,015	0	0,000	0,037	157.732	153.315	YES	0	
OCT	D2	0,114	0	0	0,000	0,034	14.328	13.770	YES	0	
OCT	D3	0,129	0,029	0	0,072	0,107	154.437	153.900	YES	0	
OCT	D4	0,044	0,017	0	0,000	0,024	249.991	238.815	YES	0	
OCT	D5	0,021	0	0	0,000	0,006	306.534	288.180	YES	0	
OCT	D6	0,077	0,085	0	0,163	0,191	118.609	121.950	**NO**	121.950	**12,57%**
NOV	D1	0,090	0	0	0,000	0,027	150.202	144.540	YES	0	
NOV	D2	0,090	0	0	0,000	0,027	13.492	12.870	YES	0	
NOV	D3	0,132	0,006	0	0,046	0,075	153.362	150.300	YES	0	
NOV	D4	0,046	0,005	0	0,000	0,017	242.117	229.608	YES	0	
NOV	D5	0,009	0	0	0,000	0,003	289.153	270.855	YES	0	
NOV	D6	0,059	0,057	0,015	0,199	0,192	130.082	130.725	**NO**	130.725	**13,92%**
DEC	D1	0,068	0	0	0,000	0,020	143.456	137.115	YES	0	
DEC	D2	0,054	0	0	0,000	0,016	12.307	11.610	YES	0	
DEC	D3	0,152	0,015	0	0,046	0,087	149.189	148.050	YES	0	
DEC	D4	0,044	0	0	0,000	0,013	257.525	243.270	YES	0	
DEC	D5	0,005	0	0	0,000	0,002	318.601	298.080	YES	0	
DEC	D6	0,062	0,054	0	0,199	0,191	148.204	148.770	**NO**	148.770	**15,07%**
								12.516.987		1.276.505	**10,20%**

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