LUT School of Business and Management

Industrial Engineering and Management

Cost Management

Credit Risk Factors in Shopping Center Industry

Master's Thesis

December 4, 2017

Henri Paukkonen

Supervisor: Timo Kärri

Supervisor: Tiina Sinkkonen

ABSTRACT

Author: Henri Paukkonen

Title of thesis: Credit risk factors in shopping center industry

Year: 2017 **Location:** Espoo, Finland

Master's thesis. Lappeenranta University of Technology, Industrial Engineering and Management, Cost Management.
69 pages, 14 tables, 4 figures ja 7 appendice
Thesis supervisors: Professor Timo Kärri, University lecturer Tiina Sinkkonen

Keywords: Shopping center, credit risk, default, logistic regression

The purpose of this master's thesis is to find the factors affecting shopping center tenants' ability to pay rent. The aim is to present a comprehensive picture of the credit risks in the shopping center industry and create a tool to help shopping center management monitor the tenants.

This thesis is a quantitative research based on internal data from the case company. The data is reviewed and analyzed with logistic regression, resulting in a mathematic model. Shopping center management can monitor and evaluate the default risk of tenants by applying the model. The model is used as a tool to evaluate financial risks, as well as to recognize tenants with high risk of default before the actual default.

The crucial factors increasing the default risk according to the regression analysis are decreasing credit rating, increasing occupancy cost ratio, and decreasing sales per leased area. Additionally, default risk is affected by company type, sales category, and whether the company is an anchor.

TIIVISTELMÄ

Tekijä: Henri Paukkonen

Työn nimi: Luottoriskitekijät kauppakeskusalalla

Vuosi: 2017 **Paikka:** Espoo

Diplomityö. Lappeenrannan teknillinen yliopisto, tuotantotalous, Kustannusjohtamisen koulutusohjelma.
69 sivua, 14 taulukkoa, 4 kuvaa ja 7 liitettä
Tarkastajat: Professori Timo Kärri, yliopisto-opettaja Tiina Sinkkonen

Hakusanat: Kauppakeskus, luottoriski, maksuhäiriö, logistinen regressio

Tämän diplomityön tavoitteena on selvittää keskeiset tekijät, jotka vaikuttavat kauppakeskusvuokralaisten vuokranmaksukykyyn. Tarkoituksena on esitellä yleiskuva luottoriskeistä kauppakeskusliiketoiminnan näkökulmasta, sekä luoda työkalu kauppakeskusjohdolle vuokralaisten seurantaan.

Työ on kvantitatiivinen tutkimus, joka perustuu case-yrityksen sisäiseen aineistoon. Aineisto käydään läpi ja sille tehdään logistinen regressioanalyysi, jonka tuloksena syntyy matemaattinen malli. Mallia soveltamalla case-yrityksen kauppakeskusjohto voi seurata ja arvioida vuokralaisten maksuhäiriöriskiä. Mallin toimii kauppakeskusjohdon apuvälineenä taloudellisten riskien arvioinnissa, sekä auttaa tunnistamaan suuren luottoriskin vuokralaiset ennen maksuhäiriöitä.

Keskeisimpinä maksuhäiriöriskiä kasvattavina tekijöinä voidaan regressioanalyysin perusteella nähdä vuokralaisen laskeva luottoluokitus, kasvava vuokran suhde liikevaihtoon sekä laskeva liikevaihdon suhde vuokrattuun liikepinta-alaan. Lisäksi maksuhäiriöriskiin vaikuttaa yritysmuoto, myyntikategoria sekä se, onko kyseessä ankkurivuokralainen.

ACKNOWLEDGEMENTS

This master's thesis has been one of the most interesting and rewarding projects I have done. It's easy to see why LUT is considered one of the best universities in Finland, with its great atmosphere and academic success. However, my journey in LUT is truly coming to its end, and my time in Lappeenranta has been amazing.

I'm grateful for the case-company for this interesting topic and their data to make this research possible, for my employer for providing me this opportunity to work on this thesis, and for all my colleagues for encouraging me in my studies. I would especially like to thank my supervisors Timo Kärri and Tiina Sinkkonen for guiding me through this project.

Most of all, I want to thank my family for supporting me during my studies and being always there for me. Thank you to all my friends and the amazing people I have met in the last few years, you have made this the best time of my life, leading to an even better future.

Espoo, December 4, 2017
Henri Paukkonen

TABLE OF CONTENTS

APPENDICES

1 INTRODUCTION

There are certain risks in every industry. Real estate industry in itself is fairly unique, with profits coming from rental payments and sales profits from developments. Thus, the crucial risks in day to day operation are the state of the property and the tenants' credit risk. For shopping centers, recognizing the tenant risk as a whole is essential. Tenant risk consists of non-payment and non-performance of other contractual obligations (Wyatt, 2013). This thesis focuses on the non-payment aspect of tenant risk, i.e. risk of default, with the aim of helping shopping center management recognize tenants with high risk, as well as to provide a tool to recognize early warnings for struggling tenants.

1.1 Background

Shopping center industry is not widely researched in Finland, with most studies and statistics are made by the Finnish Council of Shopping Centers and KTI (Property Information). Additionally, the academic literature concerning shopping center industry mostly studies the US and UK markets, with very few focusing on the main risks of the industry.

The Finnish economy has been falling behind the other Nordic countries for a few years after the Great Recession, with the Finnish GDP per capita decreasing each year between 2012 and 2015 (World Bank, 2017). As Finnish customers spend less than for example their Swedish counterparts, the shopping centers in Finland are clearly affected compared to Sweden (Smith, 2009), through the weakened ability to pay rent. Tough economic times and global trends, e.g. e-commerce, put the success of shopping centers under a lot of pressure (Achenbaum, 1999; International Council of Shopping Centers, 2015). These factors force the shopping center management and leasing to make the best decisions possible to keep the shopping center successful.

The most influence the management can have on in a shopping center, are the tenants. Thus, the tenant mix should be optimal, and the specific tenants should be successful with solid products or services, and as small risk of default as possible. The default risk should be recognized as early as the leasing phase with background information such as credit rating, sales category, as well as local and global trends, and the potential tenant's ability to survive tougher times. The changes in the default risk should also be recognized within the lease period. This includes observing the development of the tenant's turnover and credit rating, and then reacting appropriately to especially negative changes. Negotiating with the tenant, whose default risk has risen, is important in order to exercise potential lease termination clauses or providing discounts, in object of the success of the shopping center.

The increased reporting and inspection of credit losses in the case company has created the need for a tool to help shopping center management recognize the risky tenants before they default. The correct early warnings can increase the communication between the tenants and landlords, leading to less financial problems for both the tenant and the shopping center.

The certainty of income also affects the valuation of real estate properties, as most valuation methods use rental income. Currently the most used valuation methods are the discounted cash flow model and the capitalization method, in both of which the rental income is a critical factor. Thus, it is crucial to analyze the income certainty. (White & Gray, 1996; Wyatt, 2013)

1.2 Objectives and research questions

The aim of this thesis is to find factors that weaken the tenants' ability to pay rent. This thesis should provide a tool that utilizes the easily observable factors, helping shopping center management recognize and potentially prevent defaults. Thus, the objective is to provide a scope of the factors leading to defaulting tenants, and a model to predict the probability of default. In addition, the aim is to recognize risky

tenants before premises are leased to them, to help reduce the overall risk of a shopping center.

Tos fulfill the objectives above, this thesis provides answers for the following research questions:

1. What kind of tenants default their obligations?
2. Which factors affect the ability to pay rent?
3. Can defaults be prevented?

1.3 Methods, materials and scope

This thesis is a quantitative case study, based on literature review, statistics, and internal data from the case company. The literature review focuses on the characteristics of the shopping center industry, credit risks, and regression analysis – drawing a comprehensive basis for the logistic regression model, which in turn is used to find the answers to the research questions. Most of the external data and statistics are provided provided by e.g. Bisnode, FCSC and KTI. These are then compared to the internal data provided by the case company, and used in the regression analysis.

The regression analysis used in this thesis is a nominal logistic multiple regression, made with analysis software SAS JMP, to estimate the probability of default for each tenant in the research data. The regression analysis is conducted with the program's Fit Model feature, which contains all analyses necessary for the logistic regression. The logistic regression and its results are presented in chapter five. The regression model is used by the shopping center management to estimate and forecast the credit risk of tenants.

The research data is lease level data from shopping centers around Finland, owned by the case company, with external data, such as credit ratings coming outside the organization. The regression analysis is made with this geographic limitation to

ensure data is readily available and homogenous within each data category. As the case company operates in multiple European countries, internal data would also be available outside of Finland, but any external data would not be similar between countries. Also the internal data can be different between countries due to e.g. legislation, taxes, and reporting principles. While the data is entirely from Finland, the findings of this research can be used in other countries as well. However, getting the most accurate results might mean making a similar regression analysis separately for other countries to take into account the different varieties of data.

1.4 Structure of the thesis

This thesis is divided into seven main chapters. The first chapter introduces the background, objectives, methods and materials, and the structure, creating a basis for the thesis.

Chapters two and three consist of literature reviews about the shopping center industry and credit risks, respectedly. These chapters provide a comprehensive depiction of these topics, to help the reader understand the characteristics of the research.

Chapters four, five and six are the empirical chapters. The research data is presented in chapter four, where the data is also compared to statistics both within and outside the shopping center industry. Chapter five introduces the theory behind the logistic regression model, and then forms the model itself. Additionally, the results of the logistic regression model are presented and analyzed in chapter five. Chapter six focuses on the application of the logistic model in practice, and what should be taken into account when trying to predict the probability of default.

Chapter seven concludes the thesis with discussion about the research and its results, highlighting the key points and problems regarding the research. In addition, proposals for further research is provided.

2 SHOPPING CENTER INDUSTRY

The shopping center industry is highly dependent on global trends (White & Gray, 1996), local and international regulation (Dawson & Lord, 2012; Myers et al. 2008), as well as the overall economy (Myers et al. 2008), partly due to some retail industries, primarily specialty stores and entertainment, being significantly affected by dropping consumer spending (Smith, 2009). Due to the industry being affected so greatly by different factors, it has been constantly developing to keep performing. New trends, such as e-commerce, are putting landlords under pressure to make the right leasing choices, but also creating more possibilities for retailers. (Achenbaum, 1999; International Council of Shopping Centers, 2015) However, according to International Council of Shopping Centers (2015), nowadays over 90 percent of retail sales in Europe still occurs in physical stores.

For a shopping center investment, it is important to define a suitable location and analyze its catchment area, which is connected to the area's economy, as well as the location's accessibility. These factors affect the sales in the shopping center, creating the base of the shopping center performance. Investors and developers are nowadays forced to work closely with municipalities, local authorities and architects to enable the best possible accessibility via public transport and fitting in with city planning, along with public services provided in the center. (International Council of Shopping Centers, 2015)

Tenant mix is the combination of different types of stores and their price levels in a shopping center (Dawson & Lord, 2012; Cope, 1999; Yiu & Xu, 2012). The tenant mix is often lead by anchor tenants, usually large grocery and fashion stores, which have better lease terms than non-anchors. The role of the anchor tenants is to create customer flow, also helping the non-anchors. (Calanog & Marsh, 2009; Cho & Shilling, 2007; Gould et al. 2005; Sirmans & Guidry, 1993) Anchor tenants are important to the shopping center, as according to Gatzlaff et al. (1994), the loss of an anchor tenant will significantly drop the rents of remaining tenants and cause excessive vacancy, especially in small centers. Vacancy especially is dangerous to

shopping centers, as it can affect the whole center's attractiveness and therefore lower the footfall (Hutchison et al. 2008).

Finding the right tenant mix is essential for shopping centers. The optimal tenant mix will create the most customer flow, increasing the tenants' sales, and making the center as profitable as possible. This requires catchment area analysis and negotiating skills to accomplish good and wanted tenants with favorable lease terms and rents. (Carter, 2009; Cope, 1999; Yiu & Xu, 2012) The optimal tenant mix isn't necessarily the most kinds of different retail types, but it largely depends on the size, type and location of the shopping center (Yiu & Xu, 2012). It is also important to acknowledge that the optimal tenant mix changes over time, as trends and customer behavior change (Cope, 1999).

2.1 Development of the shopping center industry

Shopping centers have been developing constantly, especially after the World War II. One of the leading factors on the industry's growth was cars, as they allowed better accessibility to the shopping centers, creating more customer flow and sales. (Carter, 2009) While private vehicles boosted the development of suburban malls, the growing trend of public transportation has been a driving factor for growth in urban areas (Carter, 2009; Goedken, 2006). According to Lowe (2005), regulation clearly tightened, especially in the UK, regarding retail space outside city centers in the 1990s, further enhancing the industry's development in urban areas.

Shopping centers became the most successful retail establishments of the 20th century (Carter, 2009), affected by the most influential trends over the last 50 years as defined by International Council of Shopping Centers (Goedken, 2006):

1. Increase of real estate investment trusts, REITs
2. The enclosed mall coming into its own
3. Better access to consumer credit
4. Online retail

5. Lifestyle centers
6. Institutional investors entering the shopping center industry
7. Suburban highway intersections becoming favorable locations
8. Discount department stores
9. Power centers, a type of open-air center
10. Convenience driving consumer traffic

In Europe, gross leasable area has continually grown in the last few decades, most of which is developed by multinational companies. This has increased competition, which along with increased regulation has led to more sophisticated shopping centers. This competition has created a new trend of localizing shopping centers, while taking in attributes from other successful centers in Europe and US. On the other hand, international retail brands, such as Zara, H&M and Esprit have been spreading across Europe, perhaps making shopping centers more homogenous. (Myers et al. 2008) This competition has led to more brand marketing of the shopping centers (Myers et al. 2008; Ardill 2006), meaning shopping centers must differentiate themselves with their environment and atmosphere.

Table 1. Finnish tenant mix by sales category (Finnish Council of Shopping Centers, 2010, 2017).

Sales type	Percentage of number of shops, 2010	Percentage of number of shops, 2017
Fashion	24,7 %	26,1 %
Cafés and restaurants	13,8 %	16,9 %
Furnishing, home décor and supplies (Home)	13,3 %	11,0 %
Health and beauty	13,1 %	12,8 %
Specialty retailers	10,4 %	8,1 %
Leisure	9,0 %	8,5 %
Grocery stores	4,8 %	4,9 %
Department stores	1,1 %	1,5 %
Other commercial services	(incl. public services) 9,8 %	9,3 %
Public services	-	1,0 %

Table 1 represents the average tenant mix in Finnish shopping centers in 2010 and 2017. A clear trend can be seen with the relative number of cafés and restaurants increasing in the expense of home supplies and specialty retailers. This is also

supported by studies made in the Nordic countries (International Council of Shopping Centers, 2016) and in Europe (Myers et al. 2008), stating that shopping centers are becoming more social spaces than just utilitarian places. Additionally, according to International Council of Shopping Centers (2017), the space dedicated to food has been rising from 5 % to 10 – 15 % in a decade, and should continue to rise to 20 % by 2025 in Europe.

2.2 Shopping centers today

In recent years, entertainment has found its way to shopping centers. They have become places to spend time with movie theaters, events and fitness centers becoming cornerstones in attracting people to the centers. (Goedken, 2006; Myers et al. 2008) Additionally, Sit et al. (2003) and El-Adly (2007) recognize entertainment in shopping centers as a marketing strategy to attract more customers, as it can be used as a potential differentiator. Also finding their place in shopping centers are municipality services, such as public health care and libraries (International Council of Shopping Centers, 2015), making accessibility, and therefore public transportation more crucial.

With smartphones being an everyday tool along with social media, shopping centers have been starting to use them as tools to entice and bind customers with social media marketing and center-specific applications mostly with the cooperation of the tenants (International Council of Shopping Centers, 2015). Applications and social media can be used to inform potential customers about offers and events, as well as offering discounts and other benefits, such as free parking.

Consumers nowadays want quality and convenience, but on the other hand, also value and good prices, becoming more and more polarized in their shopping behavior (Myers et al. 2008). This along with the fact that shopping is not necessarily the main reason to come to a shopping center (El-Adly, 2007; International Council of Shopping Centers, 2015), makes finding the right tenant mix more complex and therefore more important than ever.

2.3 Rent determination in shopping centers

Determining the correct rent for each tenant in a shopping center requires analyzing the tenant mix and the spaces available, while taking into account the landlord's net rental income (Phelan, 2000). Optimizing the tenant mix includes choosing the right tenant of the right size, selling the right product at the right spot (Des Rosiers et al. 2009), and the goal should be to maximize the center's overall sales (Wheaton, 2000). The main factors to be taken into account in determining rental levels in shopping centers are presented in Table 2. These factors are mostly from the landlord's perspective, and do not necessarily take into account the bargaining powers of the two negotiators, which can have a significant impact on the resulting rent.

Table 2. Rent determination factors.

Factor	Effect on rental level
Sales category	The sales category should first and foremost match the pursued tenant mix (Des Rosiers et al. 2009). However, different sales categories have different acceptable rental levels, as they can have very different gross margins (Des Rosiers et al. 2009; Tay et al. 1999; Wyatt, 2013). Better diversification of different sales categories allows higher rents. If the shopping center is focused on only couple of categories, customer demand might not match the supply, lowering the sales of each tenant. (Des Rosiers et al. 2009)
Size of space	Base rent should be inversely related to store size, i.e. rent per square meter should decrease when store size increases (Benjamin et al. 1992; Phelan, 2000; Tay et al. 1999).
Location of space	Proximity to anchors and entrances means more customer flow and usually higher sales, which in turn should raise the rental level (Phelan, 2000; Tay et al. 1999).
Shopping center size	Larger shopping centers usually have a steadier and larger footfall, enabling higher rental level (Gatzlaff et al. 1994; Raslanas & Lukošienė, 2013; Sirmans & Guidry, 1993).
Shopping center attributes	While older shopping centers may not be able to yield as high rental levels as newly developed centers (Sirmans & Guidry, 1993), improvements and partial developments to the existing center affect rental levels positively (Des Rosiers et al. 2009; Tay et al. 1999).
Shopping center location	Location with a large catchment area and good accessibility increases footfall in the shopping center, raising the acceptable rental level (International Council of Shopping Centers, 2015). Rents in urban areas, where less land is available, also tend to be higher (Raslanas & Lukošienė, 2013).
Tenant role (anchor / non-anchor)	Better known retailers with good brands attract more customers to the shopping center, which allows them to have lower rent, while those dependent on the customer flow created by anchors should pay higher rent (Calanog & Marsh, 2009; Raslanas & Lukošienė, 2013; Wheaton, 2000).
Tenant size	Large chain stores generally have lower probability of default, enabling them to have lower rent level (Benjamin et al. 1992). According to Grenadier (1996), the rental level of national chains can be as low as half the rent of independent stores.
Vacancy	Less vacancy typically means more demand for the premises, elevating rental levels (Raslanas & Lukošienė, 2013).
Storefront size	Larger storefront attracts more customers to the store, increasing sales and therefore enabling higher rent (Phelan, 2000).
Lease length	Longer leases ultimately have higher rent due to indexations and other rent reviews (Des Rosiers et al. 2009; Raslanas & Lukošienė, 2013). Longer leases might however require lower rental level to commit to cooperation, in case large outfitting work is needed in case of tenant changes (Wheaton, 2000).

In addition to the factors presented, any renewal or break options on the lease agreement can have considerable impact on the rental level (Benjamin et al. 1992).

As there are so many different variables, there is no universal solution to determine correct rent. This requires the rental levels to be analyzed separately for each unit and tenant. (Phelan, 2000)

If a shopping center's or an individual tenant's customer flow drops, rental discounts or changes in the rental levels might be needed to balance the decreased income of tenants (Des Rosiers et al. 2009; Gatzlaff et al. 1994). Shopping center managers however are usually reluctant to change the rents, allowing only short discounts (Raslanas & Lukošienė, 2013). The landlord can leverage this for better lease conditions and possibly termination of the lease if a better alternative tenant is available.

Rent determination is usually easier for older properties than newly developed, as they have a history of sales (Phelan, 2000). However, the average market rent (Rent/sqm) for a new development can be calculated by using the following formula:

$$Rent/sqm = \frac{Cost * IRR}{(1 - Vacancy) * GLA} \quad (1),$$

where
Cost = total cost of the development,
IRR = the average internal rate of return required for the project to be profitable,
Vacancy = the percentage of retail space anticipated to be vacant,
GLA = the total gross leasable area of the development.
This formula shows the average break even rent for the new development as a whole, meaning the rental income can and should be analyzed with all premises in mind. (Phelan, 2000)

Additionally, turnover rent leases in which the tenant pays a certain percentage of their store's turnover to the landlord, are the most popular lease type (Edmund et al. 2012; Grenadier, 1996; White & Gray, 1996; Wyatt, 2013). Turnover based rents overall allow the landlord and tenant to share their risk and success between each

other (Edmund et al. 2012), and getting both to benefit from higher sales (White & Gray, 1996). Usually the tenant pays a fixed minimum (base) rent regardless of their sales (Calanog & Marsh, 2009; Edmund et al. 2012; White & Gray, 1996; Wyatt, 2013), guaranteeing steady income for the landlord (Wyatt, 2013). This means the tenant pays a percentage of its store's gross sales only when the turnover exceeds the breakpoint level (Raslanas & Lukošienė, 2013; White & Gray, 1996). Alternatively, as stated by Lamy (2000), turnover rent can be a percentage of gross sales without the guaranteed base rent or with a maximum rent.

The turnover percentage is most commonly determined by gross margins for different sales categories. For example, jewelry stores have higher gross margin percentage than large groceries due to having lower variable costs. (Wyatt, 2013) Several studies (Benjamin et al. 1992; Gould et al. 2005; Wyatt, 2013) have found that the covenant strength of the tenant along with the length of the lease affect the turnover percentage. Usually large national tenants have lower percentage rate along with a lower base rent or no base rent at all (Wyatt, 2013), making the contract purely turnover based (Edmund et al. 2012). Smaller tenants, that are dependent on the customer flow created by anchors, pay higher rent and turnover percentage, which creates incentive to the landlord's actions (Wheaton, 2000). This is also evidenced by the study deployed in Lithuania by Raslanas and Lukošienė (2013), where percentage rent varied between 3 and 7 percent, sometimes over it, with anchors having the percentage even as low as 1 to 3 percent.

Because percentage rents usually have a breakpoint level in which the turnover based rent is activated, and any turnover under that level leads to the tenant paying only the minimum rent, this can lead to tenants underreporting their sales. Underreported sales can be detected by comparing the tenant's sales trend to the whole industry or the shopping center, observing rapid changes in sales or the sales not being affected by large changes in footfall, or analyzing the reported sales proximity to the breakpoint level. (White & Gray, 1996) The monitoring of reported sales does also cause additional administrative costs for the landlord (Edmund et al. 2012). Large retail chains usually report their sales levels correctly due to their

responsibilities for their parent company. Smaller tenants most often do not have similar accountabilities which can lead to underreporting the sales. The turnover monitoring can however be enhanced by requiring an outside auditor's confirmation to their report. (White & Gray, 1996)

3 CREDIT RISKS

Credit risks in the shopping center industry can be divided into two categories: systematic risks and specific risks (Hutchison et al. 2010; Investment Property Forum, 2015). Systematic risks generally refer to the entire market or economic situation and are almost entirely unavoidable (Investment Property Forum, 2015). These risks include general economic conditions, finance rates, taxation levels and legislation changes (Hutchison et al. 2010). Of the systematic risks, the overall economic situation and changes in it has the most effect on shopping center industry, as consumer behavior and the market trends change (Giannotti & Mattarocci, 2008; Giesecke & Kim, 2011; Investment Property Forum, 2015; Myers et al. 2008; Smith, 2009). As seen in the 2009 global financial crisis, massive turmoil in the financial sector can cause stress all over the economy (Giesecke & Kim, 2011). Large scale defaults in any industry can affect the rest massively, making the shopping center industry very vulnerable to large financial crisis (Giesecke & Kim, 2011; Investment Property Forum, 2015; Smith, 2009).

Specific credit risks are unique to an asset or tenant, independent of other properties (Investment Property Forum, 2015), and are typically more significant than systematic risks (Hutchison et al. 2010). Specific risks include tenant qualities, shopping center location, rental growth prospects, the condition and potential obsolescence of the property, leasing risk and lease arrangements (Hutchison et al. 2010). In their study deployed in Italy, Giannotti & Mattarocci (2008) recognize tenant's revenue and liquidity as the most significant factors regarding tenant risk. Other major factors regarding specific risks include the type and attributes of the center, characteristics of the local area, and the overall facilities of the retail space.

For a shopping center, the reliability of the cash flow is a large factor in determining the center's value (Hutchison et al. 2008), and the center's performance depends on the ability of all tenants to pay rent according to their contracts (Giannotti & Mattarocci, 2008; Sing & Tang, 2004). According to Hutchison et al. (2010) the stability of income is key, but it is threatened by tenant default especially during the

down phase of the property cycle, as the whole property's attractiveness and therefore footfall and sales might decrease.

Defaults in shopping centers occur fairly often due to the wide spread of different tenants. However, the overall effect of an individual default is usually low in a shopping center, where the risk is divided between all of the tenants. (Hutchison et al. 2008; Investment Property Forum, 2015) This leads to shopping center industry bearing smaller overall risk for tenant defaults compared to other investment industries (Hutchison et al. 2009). The divided risk of default is especially true with larger shopping centers, where the relative rental income from a single tenant is low. This allows owners to take on extra risk in large centers, albeit not for anchors. The effect on smaller and not-so-easily leasable centers is much larger, as even individual defaults might cause shortage in the center's cash flow for a longer period of time. (Hutchison et al. 2008)

In the event of a tenant missing its payments and leaving the retail premises empty, it is usually beneficial for the lessor to terminate the lease agreement and try to lease the premises forward, minimizing the effect of spillover (Miceli et al. 2009). However, tenant losses can cause considerable losses in legal fees, tenant inducement and leasing, and marketing (Hutchison et al. 2010). This emphasizes the balancing needed in shopping center management. While it is not necessarily beneficial to keep a defaulting or otherwise "bad" tenant, losing them might mean months of lost rental income along with leasing costs, new rent-free periods, and lower rent level for the new tenant (Calanog & Marsh, 2009; Sing & Tang, 2004). Additionally, the outfitting of shopping center premises requires considerable sunken costs and they are most often tenant-specific. This causes early terminations to not necessarily be beneficial. (Wheaton, 2000)

3.1 Financial sustainability of tenants

While tenants' revenue and liquidity play a major role in the tenants' ability to pay rental in time (Calanog & Marsh, 2009; Giannotti & Mattarocci, 2008), there may

only be limited information available about the tenants' overall financial situation (Schmit, 2004), especially with smaller retailers. However, almost all retailers in Finnish shopping centers must report their monthly sales and visitors as defined by the Finnish Council of Shopping Centers (1997). This gives the landlord an effective tool to analyze the tenants' financial situation. With monthly sales information, the landlord can calculate the tenants' occupancy cost ratio (OCR), which is defined by the International Council of Shopping Centers (2005) as: "Comparison of a retailer's annual sales volume to its annual occupancy costs (including base and percentage rent, real estate taxes, common area maintenance (CAM), building insurance, and marketing/promotion funds), expressed as a percentage." Specified from this quote, the occupancy costs are defined as: "The sum of a tenant's fixed rent, percentage rent, and add-ons. Also called total rent." (International Council of Shopping Centers, 2005)

Occupancy cost ratio expressed as a formula (International Council of Shopping Centers, 2005):

$$OCR = \frac{Total\ occupancy\ cost}{Sales\ excl.VAT} * 100\ \% \qquad (2)$$

OCR can be an important tool to help determine the rental level's sustainability (Daniels & McDonnell, 2003) by measuring the financial pressure experienced by the tenant (Lamy, 2000). According to Steffen Hofmann (2015), founder and CEO of retail asset management advisor iMallinvest Europe GmbH, OCR is the most relevant performance indicator as it shows the lease agreement's true value from the tenant's perspective. Relatively low OCR is sustainable from the tenant's point of view. This also creates a buffer in case the sales drop in a market downturn. (Daniels & McDonnell, 2003) On the other hand, higher OCR means higher yield for the landlord (Phelan, 2000).

Tenant's ability to pay rent is linked to the volume of sales and the gross profit margin. This means different sales categories may have very different sustainable levels, with higher gross margin categories being able to take on higher OCR

percentages. (Hofmann, 2015; Lamy, 2000) Additionally, tenants in centers with high sales volume per occupied area may have higher OCR due to their cost structure being different within the stores compared to centers performing weaker (Daniels & McDonnell, 2003; Hofmann, 2015; Phelan, 2000).

Table 3. Sustainable OCR levels in literature.

Author	OCR-%	Costs and comments
Calanog & Marsh (2009)	Department stores and supermarkets: 2-3 % Other major tenants: 5-7 % Minor tenants: 7-10 %	Includes base rent and expense reimbursements
Daniels & McDonnell (2003)	OCR when the average comparable shop sales per sqm in whole center: < $250: 9 – 11 % $250 - $300: 11 – 13 % $300 - $350: 13 – 14 % > $350: 14 – 16 %	OCR for whole center calculated by dividing the total occupancy costs by the total sales
Hofmann (2015)	13 – 15 % generally, even 17 % in massive successful centers Groceries: 3,5 – 5 % Furniture stores: up to 20 %	Substantial differences between sales categories, also varying between countries and the success of the center
Phelan (2000)	10 – 15 % in a regional shopping center	Costs include rent, CAM, taxes and marketing fee
White & Gray (1996)	10 – 15 %	Not specified further

As seen in table 3, there doesn't seem to be a consensus in literature regarding sustainable OCR level. Additionally, the stated OCR levels are not necessarily justified by the authors. Some authors only provide general guidelines (Phelan, 2000; White & Gray, 1996), while some recognize the differences between sales categories (Calanog & Marsh, 2009; Hofmann, 2015) and different centers (Daniels & McDonnell, 2003; Hofmann, 2015). The sustainable OCR levels also have wide ranges within recommended levels with the highest percentage being 1,5 to 5 times the lowest.

3.2 Credit ratings

Credit scoring models are used to assess credit worthiness, and their objective is to assign credit risk to either a "good risk" group that likely follow their financial obligations or a "bad risk" group that has high possibility of defaulting on their obligations. Developed since 1940s, the use of credit ratings has widened broadly in the following decades, going from personal credit granting processes to personal loan approvals all the way to a wide array of business applications, becoming a key component in financial institutions' risk management. (Lopez & Saidenberg, 2000; Yap et al. 2011) Even though credit scoring is mostly used for loan applications, it can easily be used in real estate leasing to predict late payments and defaults. (Yap et al. 2011) Low credit ratings and its changes in the past are considered to increase the tenant's credit risk. (Hutchison et al. 2008) It should be kept in mind that usually credit ratings do not take into account the market risk (Lopez & Saidenberg, 2000), which in the shopping center industry can have a major effect.

Credit ratings are usually performed by credit rating agencies to provide the information to customers in need of credit rating information as well as other institutions that use the rating for their own needs, such as banks, insurance companies, and investment funds (Lopez & Saidenberg, 2000; Renigier-Bilozor et al. 2017). Most credit rating models can differ from each other in their definitions of credit losses and other assumptions (Lopez & Saidenberg, 2000). The popularity of credit rating use in different business areas grows all the time as it is used as a vital source of information about the entity's financial standing and the risk of bankruptcy and default (Renigier-Bilozor et al. 2017), and can be used to measure risk-adjusted profitability (Lopez & Saidenberg, 2000).

Europe's leading digital business information provider Bisnode was the leading developer of AAA-Rating model. This model is widely used especially in the Nordic countries to measure credit risks of companies. This model automatically analyzes the company's activity, background, finance and payment behavior to estimate its credit worthiness and ability to follow its financial obligations. This

allows the model to be real-time, as opposed to most credit rating models, which evaluate credit worthiness in intervals or when separately calculated. (Bisnode, 2017b)

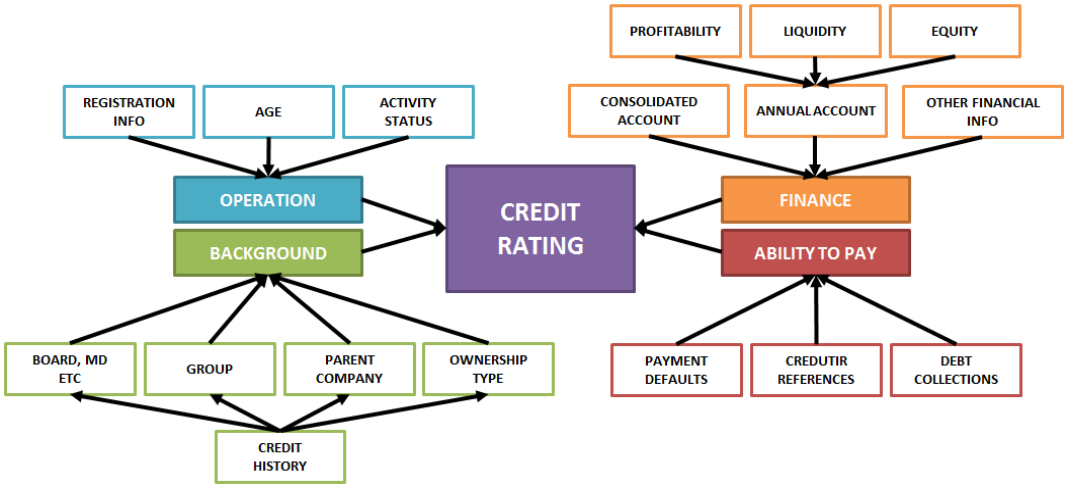


Figure 1. AAA-Rating model (Bisnode, 2017b).

Gathered data affects different areas of the credit rating estimation as seen in Figure 1. If the company's operation is established (active with history of more than 2 periods), it affects the rating positively. Newly established operation and unconfirmed activity are neutral towards the rating, while passive, liquidated or dissolved operations are negative. The credit history of the company's background also affects the overall rating, and it is comprised of parent company or group, and the company's ownership. The finance part of the equation compares the company's crucial financial ratios to the industry average, taking into account the age of the ratios. The ability to pay is measured by the number of payment remarks, payment delay, and trade experiences from businesses dealing with said company. (Bisnode, 2017b)

Table 4. Credit ratings (Bisnode, 2017a, 2017b).

Rating	Explanation	% of all companies	% of limited companies	% of other companies
AAA	Highest creditworthiness	3,5 %	8,1 %	> 0,1 %
AA	Good creditworthiness	14,4 %	25,5 %	6,1 %
A	Creditworthy	56,9 %	35,8 %	72,0 %
AN	New company with positive background	9,3 %	8,3 %	10,1 %
No rating	Information lacking or conflicting	3,9 %	4,8 %	3,9 %
B	Credit against securities	6,9 %	8,5 %	5,8 %
C	Credit rejected	5,1 %	9,0 %	2,2 %

Bisnode divides companies into seven credit rating categories shown in table 4. Of all Finnish companies in Bisnode's database, almost 75 percent are creditworthy, as in a credit rating of at least A. Nonetheless, the difference between limited companies and other companies is substantial as the ratings of limited companies are distributed more evenly across different ratings, while over 70 percent of other companies have a credit rating of A. (Bisnode, 2017a)

Table 5. Average credit rating.

		% of companies			Total points		
Rating	Points	All	Limited	Other	All	Limited	Other
AAA	4	3,5 %	8,1 %	> 0,1 %	0,140	0,328	0,001
AA	3	14,4 %	25,5 %	6,1 %	0,431	0,763	0,183
A	2	56,9 %	35,8 %	72,0 %	1,137	0,716	1,439
AN	1	9,3 %	8,3 %	10,1 %	0,094	0,083	0,101
-	0	3,9 %	4,8 %	3,9 %	0	0	0
B	-1	6,9 %	8,5 %	5,8 %	-0,069	-0,085	-0,058
C	-2	5,1 %	9,0 %	2,2 %	-0,101	-0,179	-0,043
Total					1,631	1,625	1,623

According to Hutchison et al. (2008), limited companies generally have lower risk profile than non-limited companies. Also, large firms, usually limited companies, are typically more concerned about their credit rating, leading to higher credit ratings (Graham & Harvey, 2001). However, these statements do not fully reflect on Bisnode's credit rating information. With the data presented in Table 4, the average credit rating of different company groups can be calculated by giving 4 points for AAA ratings, 3 points for AA, 2 points for A, 1 point for AN, 0 points for No rating, -1 points for B and –2 points for C. These points are multiplied by

the respective percentages and added together as seen in Table 5. This simple calculation shows limited companies having very similar average credit rating than other companies in Finland, with the average being just below A rating level for both company types. On the other hand, it is possible that different ratings do not have a linear connection between each other, which would alter the average credit rating calculation.

3.3 Minimizing credit risk

The risk of tenant default should be taken into account when leasing shopping center's retail premises. Credit risks can be dealt with different agreement clauses and conventions, such as termination clauses, collaterals and up-front payment (Grenadier, 1996). One of the most effective risk minimization means is the introduction of rental collaterals (Grenadier, 1996; Hutchison et al. 2010; Schmit, 2004). This means the tenant paying a deposit to the lessor or to an external bank account or purchasing a guarantee from a bank or other institute, such as the tenant's parent company. The landlord is usually allowed to withdraw the deposit partially or wholly to cover: overdue rent or other charges, costs incurred by breach of contract (opening times etc.), and repairs caused by tenant (changing of locks etc.). Deposits most often allow the landlord "immediate access" compared to monetizing a bank guarantee, which requires formal enforcement procedures. (Hutchison et al. 2010)

If there is no deposit or guarantee in place, the loss of income is immediate with default until the premises are repossessed and leased again. Deposit system is needed the most in recession, and then getting tenants to deliver them might be problematic, as their business is uncertain or they cannot get a financial institute to guarantee them. This suggests that landlords should insist the deposits at the rise or height of the market to cover any losses in the down phase. (Hutchison et al. 2010) This can also be prevented by requiring a deposit for every lease agreement that fulfill certain criteria. According to Hutchison et al. (2010), the amount of the collateral can vary from two months' worth of gross rent in USA, three to six

months' gross rent in Europe, and up to ten months' worth of gross rent in Asian developed countries.

Lamy (2000) lists ways to notice potential bad debt tenants:

- Erratic payment trends: Irregular lump-sum payments on accounts rather than the invoice amount paid with the correct references
- Established companies never been worked with: If they have no reason to move from their previous location
- Industry trends: More frequent bankruptcies may indicate a downturn, requiring more oversight
- Watching out for news or reports about problems with your tenants

Credit risks can also be mitigated by introducing a rental premium for tenants with higher risk. The lessor should also alter the contract terms and length of high risk tenants. (Ambrose & Yildirim, 2008; Grenadier, 1996) Introducing risk premiums could however cause more defaults as the high-risk tenants may not have the financial stability to pay increased rent. As noted by Jarrow et al. (1997), the longer the lease term, the more likely the tenant is to default. Thus, a shorter lease for higher risk tenants might be more suitable, which in turn requires more work to be done considering the leasing, also causing vacancy and possible fit out costs. Perhaps the best way to reduce the overall tenant default risk is to - already in the rising phase of the market - differentiate the preferred tenants already from those likely to default during market downturn (Sing & Tang, 2004).

4 INPUT DATA

The input data analyzed in this thesis is lease level data combined with charge and payment data from the case company as well as credit rating information provided by Bisnode. The data used in this thesis is from between March 2015 and June 2017, consisting of 597 tenants from multiple shopping centers in Finland. The tenants were chosen into the analysis if the lease agreement was valid for at least 18 months between March 2015 and June 2017, the tenant had monthly sales available for its whole tenancy period, and its credit rating was available from Bisnode. Every lease agreement is handled as its own entity, even if the same company has multiple agreements that fit the criteria.

This input data is analyzed to find correlations between different attributes and indicators of the tenants, and the risk of default. Charge and payment data is used to determine whether the tenant defaults. This is done by calculating the monthly receivables in the analysis period. The tenant is defaulting if its receivables exceed three months of gross rent at any time. The amount of three months' rent is chosen internally due to it being an average amount of collateral in Europe, as well as leases usually having termination clauses that can be used in case of large defaults.

4.1 Data categories

To be able to conduct a regression analysis, as much data as possible is necessary to recognize the most influential factors. The following data was available for the analysis:

- Monthly sales
- Monthly charges
- Monthly payments
- Size of the premises
- Anchor/non-anchor
- Shopping center region

- Sales Category
- Company type (i.e. Limited or Other)
- Credit rating

Monthly sales are the sales without VAT (i.e. turnover), reported by the tenant. Monthly charges include base rent and maintenance charges, or gross rent, and all other charges, e.g. turnover rent and marketing fee. Monthly payments are made by the tenant, and have been allocated by reference numbers and payer information.

The monthly financial data allows the calculation of receivables and occupancy cost ratio. Receivables are calculated by subtracting the tenant's cumulative payments from the total cumulative charges including VAT. This is done for the whole lease period due to most leases starting before and some of them having receivables before start of the analysis period. Occupancy cost ratio is calculated as a maximum of 12 months rolling cumulative ratio from the start of the analysis period by dividing the total turnover by the occupancy costs (base rent and maintenance charges) of the same period. OCR is calculated without VAT due to the reporting principles of the case company and different tax percentages between sales categories.

Size of the premises is the gross leasable area (GLA) of the contract, only including the retail premises. Anchor status is decided within the shopping center organization, and there usually are a few anchors in every shopping center, as described in Chapter 2. Shopping center region is divided into two categories in this thesis, Helsinki Metropolitan Area (HMA) and Other Areas in Finland. The sales categories are the ones used by the Finnish Council of Shopping Centers (2010, 2017), and tenants are divided into the categories internally within the case company. Average sales per GLA can also be calculated with monthly sales and premise size.

Company type is either Limited company or Other company, and the data is provided by Bisnode. Other companies are usually joint-stock companies, limited

partnerships, or sole traders. The credit ratings for the tenants are also provided by Bisnode, only with No rating and AN combined as No rating. The credit rating is used as a static value, and it is the rating the company had either when the lease agreement ended within the analysis period or in June 2017 if the agreement was still valid.

Of the 597 tenants in the data, 112 are anchors. All shopping centers in the data have more than one anchor, with most being ten. Additionally, 508 of the tenants are limited companies and the rest, 89 tenants, are other company types.

4.2 Preliminary analysis

The leases are divided into the same sales categories as the Finnish Council of Shopping Centers does. However, there are no public services in the data, as none of them report their sales. The distribution among sales categories is presented in Table 6, with the number of shops, total GLA, and their percentages of the whole data. Compared to the overall sales category distribution in Finland, the examined data has much lower percentage of tenant focusing on Fashion, Home (furnishing, home décor and supplies) and Other commercial services, while the emphasis is significantly larger on Leisure, Health and Beauty, and Groceries.

Table 6. Sales category distribution.

Sales category	Number of shops	Percentage of shops	GLA	Percentage of total GLA
Fashion	136	22,8 %	47 251	19,9 %
Leisure	103	17,3 %	33 916	14,3 %
Health and Beauty	103	17,3 %	19 249	8,1 %
Cafes and Restaurants	101	16,9 %	16 818	7,1 %
Groceries	53	8,9 %	76 471	32,2 %
Home	36	6,0 %	11 812	5,0 %
Specialty retailers	32	5,4 %	3 711	1,6 %
Other commercial services	21	3,5 %	11 763	5,0 %
Department Stores	12	2,0 %	16 228	6,8 %
Total	597	100,0 %	237 217	100,0 %

Table 7 presents credit rating distributions and the default percentages within the input data. The difference between all companies in Bisnode and the lease data is clear. The distributions of credit ratings as well as the defaults in different ratings are far more even. Bisnode's AN-rated companies are presented together with companies with no rating (presented as "-"), as they are also reported together in the input data, making comparisons more adequate. The 24 months probability of default according to Bisnode was chosen, as the analysis period is 22 months, making the probabilities and percentages comparable.

Table 7. Credit rating distribution comparison (Bisnode 2017).

Credit Rating	% of total number of leases in case data	% of companies in Bisnode	Defaulted leases in case data	Probability of default in 24 months (Bisnode)
AAA	11,7 %	3,5 %	2,9 %	0,8 %
AA	34,0 %	14,4 %	3,4 %	1,3 %
A	30,8 %	56,9 %	2,7 %	2,0 %
-	5,7 %	13,3 %	14,7 %	15,9 %
B	10,2 %	6,9 %	11,5 %	32,4 %
C	7,5 %	5,1 %	48,9 %	56,4 %
Total			8,0 %	8,6 %

The total number of defaults in the data is similar to the probability of default in 24 months according to Bisnode. The slight differences in the percentages might be due to the shopping centers having only retail tenants, while there are all business areas represented in the Bisnode data. However, the distribution is quite similar, showin the data is realistic.

Table 8. OCR in sales categories.

Sales category	Total OCR	Average OCR	StdDev of OCR
Cafes and Restaurants	13,1 %	14,3 %	6,0 %
Department Stores	10,4 %	10,4 %	4,5 %
Fashion	20,1 %	21,5 %	8,1 %
Groceries	6,4 %	7,4 %	8,5 %
Health and Beauty	4,4 %	14,3 %	12,0 %
Home	17,8 %	19,9 %	8,3 %
Leisure	13,7 %	17,2 %	11,1 %
Other commercial services	17,2 %	13,8 %	7,2 %
Specialty retailers	8,3 %	17,4 %	21,0 %
Total	8,9 %	16,2 %	10,9 %

Because the occupancy cost ratio differs drastically between sales categories, as presented in Table 8, it is beneficial to analyze OCR as a distance from the category average. The total OCR of the sales category is calculated by dividing the total occupancy cost with the total turnover of the whole category. However, as the purpose is to find comparable numbers between sales categories, it is best to use the category average percentage as the benchmark, rather than the category total. This is due to the fact, that there are large differences between turnover and rent amounts, which skews the total OCR values towards the large tenants.

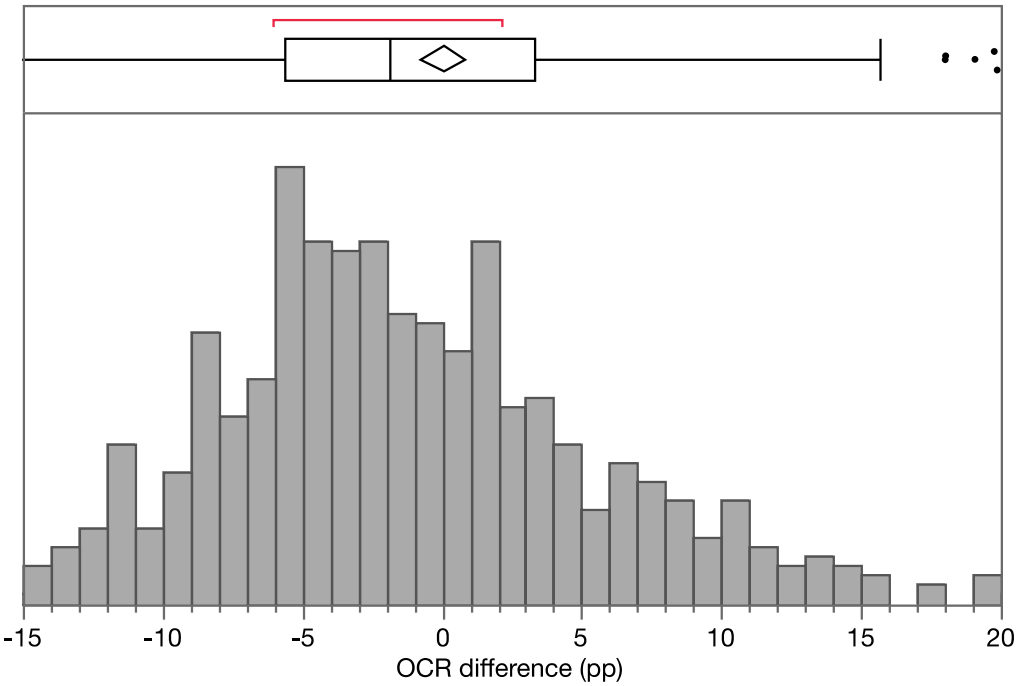


Figure 2. Distribution of OCR difference (SAS JMP).

The OCR distribution is presented in Figure 2 as a difference from the sales category average in percentage points with the relative number of leases. The graph is restricted to display approximately 95 percent of all leases to exclude the extremities. Also shown in Figure 2 is the median OCR difference is approximately -1,9 percentage points, while the mean is 0,0 pp (due to the graph representing the distance from average), and standard deviation is approximately 10 pp. The

maximum negative difference (-16,7 pp) is not shown in the figure, as is not the maximum positive difference at 84,2 pp.

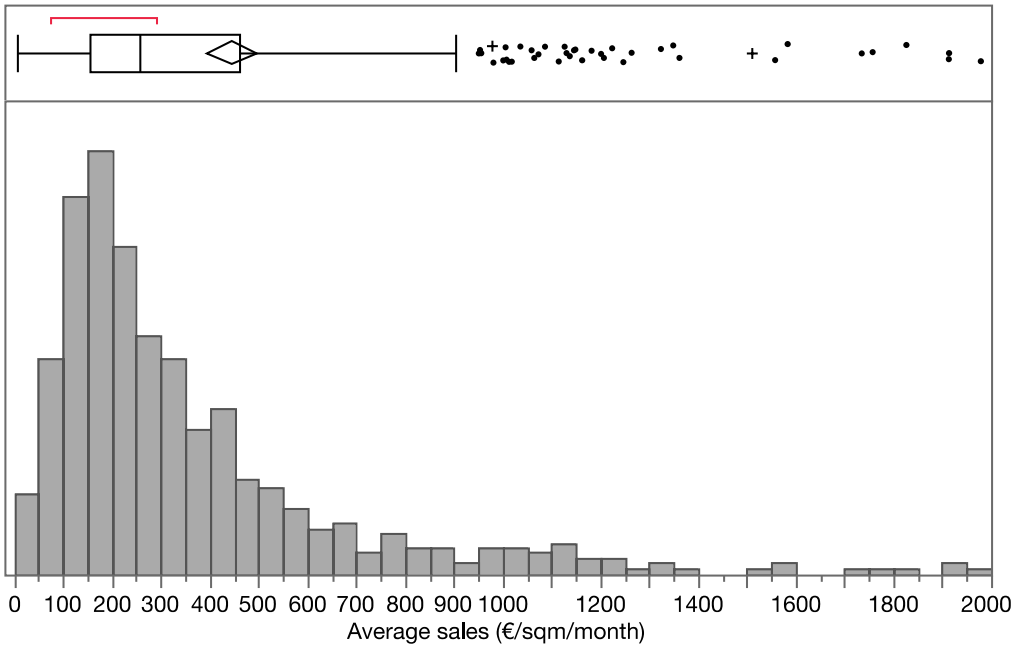


Figure 3. Distribution of average monthly sales per GLA (SAS JMP).

Figure 3 represents the distribution of average monthly sales per retail square meters in relation with the number of leases. Maximum monthly sales per GLA is approximately 5200 € and the minimum is approximately 5 €/sqm. Even though the mean monthly sales per GLA in the whole input data is 444 €, as seen in Figure 3, most of the tenants have sales below 300 €/sqm/month. This leads to the median sales being 257 €.

Table 9. Monthly sales per GLA by categories.

Row Labels	Average monthly sales/GLA	StdDev of monthly sales/GLA
Groceries	1 041,90	1206,60
Health and Beauty	647,47	778,90
Specialty retailers	467,24	398,53
Leisure	400,21	408,42
Other commercial services	382,56	309,66
Cafes and Restaurants	377,25	411,89
Home	277,28	508,11
Fashion	212,46	120,19
Department Stores	180,74	63,26
Total	444,00	610,07

Table 9 represents the average monthly sales figures for each sales category. The average sales vary greatly between sales categories further confirming the differences between categories. There is also large variance within the categories, most of which can be explained with the few extremely large average sales in most categories.

5 REGRESSION ANALYSIS

The purpose of the regression model is to find the probability of default, given multiple independent variables, that can be continuous, ordinal, or nominal. As the dependent is dichotomous, i.e. yes or no, a logistic regression model is used (Kleinbaum & Klein, 2010; Peng et al. 2002). Due to the input data being from a 22-month period, the estimated probability of default is also for a period of 22 months.

5.1 Logistic regression model

A logistic regression model mathematically models the relationship of several independent variables to the dichotomous dependent variable. A logistic function describes the mathematical form on which the logistic model is based. In the function, z is a linear variable with a range of -∞ to ∞, and is a function of the dependent variables and coefficients. When z is -∞, the logistic function equals 0, and when z is ∞, the logistic function equals 1. This characteristic of the logistic function makes the logistic model fitting to describe probability. The logistic model is also much more lenient regarding the input data, and only requires the following assumptions:

- The dependent variable is binary, with 1 as the target value
- The independent variables should be independent of each other

(Berry et al. 2016; Kleinbaum & Klein, 2010; Peng et al. 2002)

The logistic function is written as (Kleinbaum & Klein, 2010):

$$f(z) = \frac{1}{1 + e^{-z}} \qquad (3),$$

where z is the linear equation. It can be seen,that the larger the linear function, the higher the whole logistic function is. Z is the linear sum of all independent variables multiplied with constant terms to account for the differences in the variables:

$$z = a + b_1X_1 + b_2X_2 + \cdots + b_nX_n = a + \sum_{i=1}^{n} b_iX_i \qquad (4),$$

where the X_i are the independent variables, and the a and b_i are the constant terms representing unknown parameters, that need to be estimated based on the research data. As $f(z)$ is a probability function, it is best presented as $P(X)$, where $f(z)$ is combined with the z function:

$$P(X) = \frac{1}{1 + e^{-(a+\sum b_iX_i)}} \qquad (5)$$

A logit form of the model means taking the natural log of the probability P with specific X's divided with 1 minus P. The logit function ultimately simplifies to the linear sum of all independent variables:

$$logit\ P(X) = \ln\left(\frac{P(X)}{1 - P(X)}\right) = a + \sum_{i=1}^{n} b_iX_i \qquad (6),$$

which gives the expression for the log odds of the event, in this case default, happening. In the function, $\frac{P(X)}{1-P(X)}$ describes the odds ratio (OR), i.e. the ratio of the probability $P(X)$ that an event will occur over it not occurring. (Kleinbaum & Klein, 2010; Peng et al. 2002)

Further, the logit function can be used to calculate the baseline odds of the logistic model, i.e. when all X equal 0, with e^a. While there may not be any sample in the population, which has all independent values as 0. However, the baseline odds just mean the odds that the model produces without any X's, and it can be used to

compare to the effect of X's. The logit function can also be used to estimate the change in odds when one X changes by one unit and others stay constant:

$$\begin{aligned} \Delta\, log\, odds &= logit\, P_1(X) - logit\, P_0(X) \\ &= a + b_1 * 1 + b_2 X_2 - (a + b_1 * 0 + b_2 X_2) = b_1 \end{aligned} \quad (7),$$

where coefficient b_1 can be used to determine the effect one unit of change in the variable X_1 has on the total odds of the model by taking e to the power of b_1. This can be interpreted as how the entire probability of default changes, when only one of the independent variables changes by one unit. This is especially useful when estimating the effect of binary variables. However, as some of the variables are continuous, the change in X_1 can practically be anything from -∞ to ∞, and it can be taken into account by multiplying b_1 by the amount of change in X_1. Taking this possibility into account in the case of X_1 being continuous, makes the change in the total odds of the model $e^{b_1 \Delta X_1}$. Further, the change in total odds (i.e. how many times more probable is a default with the changes) when multiple independent variables change can be estimated with the change in the linear function z in the power of e. (Kleinbaum & Klein, 2010; Peng et al. 2002)

5.2 Effectiveness of the logistic regression model

According to Peng et al. (2002), the effectiveness of a logistic regression model must be evaluated with:

1. Overall model evaluation
2. Statistical tests of individual predictors
3. Goodness-of-fit statistics
4. Validation of predicted probabilities.

Logistic model provides better fit to the data if it shows improvement over null model, i.e. intercept-only model, where all variables equal zero. This overall model

evaluation can be tested with likelihood ratio, where the null hypothesis for the overall model is that all *b*'s equal zero. The null hypothesis can be rejected if at least one *b* does not equal zero in the whole population. This means the logistic regression model predicts the probability better than the mean of the dependent variable. The likelihood ratio itself is calculated by:

$$L = -2\ln\left(\frac{L_0}{L_F}\right) \qquad (8),$$

where L_0 is the maximum likelihood of the null model, and $L_F$is the maximum likelihood of the full model. L approximately equals χ^2, and the significance of the full model can be estimated using the χ^2 statistics and the model's degrees of freedom to get the *P*-value. (Kleinbaum & Klein, 2010; Peng et al. 2002)

Statistical tests of individual predictors is tested similarly to the whole model, with effect likelihood test. The likelihood ratio for each independent variable is estimated by using the equation 8 with the null hypothesis being that the tested variable does not have an effect on the dependent variable. Similarly to the whole model test, effect likelihood test produces χ^2 values for each independent variable, as well as the intercept. These values are then compared to the χ^2 statistic to estimate the *P*-value, and therefore the significance of each coefficient. (Kleinbaum & Klein, 2010)

The goodness-of-fit can be estimated by using McFadden's pseudo-R^2 to measure the model's uncertainty. For non-linear models, such as logistic regression models, pseudo-R^2s act similarly to R^2 for linear models. McFadden's pseudo-R^2 is calculated as:

$$R^2 = 1 - \frac{\ln(L_F)}{\ln(L_0)} \qquad (9),$$

where $\ln(L_F)$ is the maximum log-likelihood of the full model and $\ln(L_0)$ the log-likelihood of the null model, where each alternative is assigned the same probability

of being chosen. Thus, R^2 measures the model's improvement to the null model, meaning values close to one have none or very little uncertainty. However, it should be noted that McFadden's pseudo-R^2 values are generally low, as certainty in the predicted probabilities is rare for logistic models. (McFadden 1974, Sung et al. 2016)

Additionally, pseudo-R^2s do not fully represent the same as traditional R^2 in linear models, i.e. express the proportion of variation in the dependent variable, that can be explained with the independent variables. In logistic models, R^2 only gives a guidance on the goodness-of-fit (Peng et al. 2002), and it can be used to compare models from the same data with the same number of predictors (Sung et al. 2016).

Validating the predicted probabilities can be made with *c* statistic. It represents the proportion of correct predictions using the logistic model to the data set. The *c* statistic test ranges from 0 to 1, with a result of 0,5 meaning the model is no better than random assignment. The closer the result is to 1, the better the model fits the data, and more often it predicts correctly. The *c* statistic test has a cutoff point of 0,5 – i.e. the value of the model for each observation, with values over 0,5 being predicted as Yes, and values less than 0,5 being predicted as No. The cutoff point can also be specified as anything else, while keeping in mind the cutoff when using the model to new data. (Peng et al. 2002)

In the *c* statistic, the observed and predicted frequencies are put into a 2x2 table, where sensitivity and specifity is calculated, as well as the overall percentage of correct predictions. Sensitivity means the correctly predicted events, i.e. the proportion of observed events that are predicted as events. Specifity on the other hand is the proportion of correctly predicted nonevents. Overall prediction accuracy is the proportion of the total correct predictions. Additionally, false positive equals to the proportion of falsely predicted events, i.e. predicted as an event but are observed as a nonevent, and false negative is the proportion of falsely predicted nonevents. (Peng et al. 2002)

5.3 Modelling default probability

The logistic regression model was tested with SAS JMP software. The best model was searched with different combinations of independent variables with as little bias between each other as possible. In the final model, the independent variables are:

- Credit rating
- OCR difference
- Anchor
- Limited company
- Sales category
- Sales per GLA

Credit rating is a nominal variable with ratings A, AA, and AAA grouped together as "> A". This is due to them being very similar in both Bisnode description, and in default probability, with R^2 value of 0,0015 and P-value of 0,91 – meaning the difference in default probability between credit ratings A, AA, and AAA is insignificant and explains only 0,15 percent of the variation (see Appendix 1). Other possible values are "-" (as no rating), "B", and "C".

OCR difference is a continuous numeral variable measured as a distance from the sales category average in percentage points. The model could be done with OCR-%, but it would be biased with the variable sales category, leading to one of them not being able to be used. This would also lower the R^2, making the model worse at estimating the default probability.

Anchor is a binary variable. If the tenant is an anchor in its shopping center, the value is 1, and if not, the value is 0. The anchor status is decided independently within the case company by the shopping center management.

Limited company is similarly a binary variable. A limited company gets a value of 1, and a non-limited company a value of 0. As described in the previous chapter, the company type is derived directly from Bisnode.

Sales category is a nominal variable, which depends on the tenant's line of business. The sales category is decided internally within the case company. There are nine categories used in this research, and they are the same as the Finnish Council of Shopping Centers uses:

- Cafés and restaurants
- Department stores
- Fashion
- Grocery stores
- Health and beauty
- Home (Furnishing, home décor and supplies)
- Leisure
- Other commercial services
- Specialty retailers

Sales per GLA is a continuous variable measured as average monthly turnover in euros per the tenant's retail area in square meters. The average sales per GLA is the running average of 12 months' turnover in the point of default, lease end, or as of June 2017.

Table 10. Whole model test (SAS JMP).

Model	-LogLikelihood	DF	ChiSquare	P-value
Difference	47,27764	15	94,55527	<,0001*
Full	114,08613			
Reduced	161,36377			

The final model, which includes these aforementioned independent variables, is then tested with the measures presented in chapter 5.2. The whole model test is presented in Table 10. With the χ^2 value of 94,56 and 15 degrees of freedom, the

P-value for the whole model is $1{,}39 * 10^{-13}$, meaning very convincing significance.

Table 11. Effect likelihood ratio tests (SAS JMP).

Coefficient	DF	ChiSquare	P-value
OCR dist	1	2,59348804	0,1073
Anchor	1	1,80104739	0,1796
Limited company	1	0,20318234	0,6522
AVG sales/GLA	1	0,1875428	0,6650
Credit rating	3	60,1199381	<,0001*
Sales category	8	12,3036578	0,1382

Statistical tests of individual predictors is tested with effect likelihood tests, and the results are presented in Table 11. As seen in the table, only credit rating is a truly significant variable in the model, with company type and average monthly sales having *P*-values over 0,6. This indicates that they are not necessary for the model to fit the data. However, by themselves all variables used in the model have significant correlation for the default probability, as seen in Table 11 (for more detailed analysis, see Appendice II through VII). Additionally, dropping most of the predictors out of the model would cause the model not to fit the data as well, and would remove critical information when using the model in practice.

Table 12. Individual regression analyses (SAS JMP).

Coefficient	Test	R-Square	P-value	Appendix
OCR dist	Logistic fit	0,035	0,0007	2
Anchor	Contingency analysis	0,029	0,0018	3
Limited company	Contingency analysis	0,016	0,0224	4
AVG sales/GLA	Logistic fit	0,024	0,0055	5
Credit rating	Contingency analysis	0,224	<0,0001	6
Sales category	Contingency analysis	0,049	0,0367	7

How well the model fits the data is tested with McFadden's pseudo-R^2, which has a value of 0,2930 for the whole model. This means the model can explain the probability of default approximately 29,3 % better than a null model. As pseudo-$R^{2\prime}s$ most often have low values (Peng et al. 2002), it can be concluded that the model does fit the data well. There is admittedly high amount of data not available for the shopping center management, from which they could benefit in estimating

the credit risks of a tenant. These include for example profit margin, business outside the center, and other financial obligations.

The predicted probabilities of the model are tested with *c* statistic. As presented in Table 13, the final model's sensitivity is 28,3 %, i.e. the model predicts defaults correctly 28,3 percent of the time. The model's specifity on the other hand is 97,8 %, meaning the model predicts almost all non-defaulting leases correctly. Overall the model predicts 92,3 % of the defaults correctly, meaning the model is considerably better than random chance. However, the proportion of false positives is 48,0 %, which is quite high, but on the other hand, these estimations can be seen as a risk group. The proportion of false negatives is only 5,9 %, indicating the model better predicts the tenants, that are the least likely to default.

Table 13. C statistic test of predicted probabilities (SAS JMP).

Actual	**Predicted Count**		
DEFAULT	**Yes**	**No**	
Yes	13	33	28,3 %
No	12	530	97,8 %
	48,0 %	5,9 %	92,3 %

The linear function *Z* for the logistic regression model is presented in Figure 4. The effect of each variable can be seen from the model. The intercept of the model, or *a*, equals approximately -6,07; meaning the baseline odds for default are somewhat low. Further, it can be seen that the higher the OCR compared to the sales category average, the larger the linear function and therefore higher the probability of default, as expressed in equation 4. Also, the tenant being an anchor or a limited company lower the default probability. Higher average sales expectedly lower the probability of default. Credit ratings also have the expected effect, with at least A ratings having the lowest and C having the highest default probabilities. Sales categories have large differences between each other, with groceries and other commercial services being the least likely to default, and department stores the most likely. It should be noted that the sales category has a large effect on the default probability in this model, especially as groceries and other commercial services lower the probability significantly compared to other independent variables.

$$
\begin{aligned}
&-6{,}067523729 \\
&+ 0{,}0259884745 \bullet \textit{OCR dist} \\
&+ \text{Match}\left(\textit{Anchor}\right)\begin{pmatrix} 0 & \Rightarrow & 0 \\ 1 & \Rightarrow & -0{,}969301403 \\ \text{else} & \Rightarrow & . \end{pmatrix} \\
&+ \text{Match}\left(\textit{Limited company}\right)\begin{pmatrix} 0 & \Rightarrow & 0 \\ 1 & \Rightarrow & -0{,}235475783 \\ \text{else} & \Rightarrow & . \end{pmatrix} \\
&+ -0{,}000281716 \bullet \textit{AVG sales/GLA} \\
&+ \text{Match}\left(\textit{Credit rating}\right)\begin{pmatrix} \text{"> A"} & \Rightarrow & -1{,}562749046 \\ \text{"-"} & \Rightarrow & -0{,}131553442 \\ \text{"B"} & \Rightarrow & -0{,}077896961 \\ \text{"C"} & \Rightarrow & 1{,}7721994497 \\ \text{else} & \Rightarrow & . \end{pmatrix} \\
&+ \text{Match}\left(\textit{Sales category}\right)\begin{pmatrix} \text{"Cafes and Restaurants"} & \Rightarrow & 4{,}9658760924 \\ \text{"Department Stores"} & \Rightarrow & 6{,}0192596398 \\ \text{"Fashion"} & \Rightarrow & 4{,}1275424823 \\ \text{"Groceries"} & \Rightarrow & -16{,}75178239 \\ \text{"Health and Beauty"} & \Rightarrow & 4{,}6843359138 \\ \text{"Home"} & \Rightarrow & 4{,}9252247962 \\ \text{"Leisure"} & \Rightarrow & 4{,}663232771 \\ \text{"Other commercial services"} & \Rightarrow & -16{,}13439664 \\ \text{"Specialty retailers"} & \Rightarrow & 3{,}5007073259 \\ \text{else} & \Rightarrow & . \end{pmatrix}
\end{aligned}
$$

Figure 4. The linear function Z (SAS JMP).

With the intercept, the model's baseline odds and therefore base probability of default can be estimated:

$$OR_0 = e^a = e^{-6,0675} = 0,00232 \qquad (10),$$

making the base probability of default:

$$P(a) = \frac{OR_0}{OR_0 + 1} * 100\ \% = \frac{0,00232}{1,00232} * 100\ \% \approx 0,23\ \% \qquad (11),$$

which is very low, as 8 percent of the data did default. However, most of the effect on the default probability comes down to the independent variables.

As the coefficients can be used to estimate the change in total model odds with one or more variables changing, it will be beneficial to estimate some realistic events. With all other independent variables being constant, an increase of 5 percentage points in OCR increases the tenant's total odds of default by:

$$\Delta OR_{OCR}(5) = e^{b_{OCR}\Delta X_{\mathrm{OCR}}} = e^{0,0260*5} \approx 1,14 \qquad (12),$$

meaning a default is 1,14 times more likely when the OCR increases 5 percentage points.

Both anchor and limited company are static binary variables, which means they usually can't change within tenancy. This means only the comparisons between anchor and non-anchor, as well as a limited company and non-limited company can be made. By applying the equation 9, it can be estimated, that a non-anchor is approximately 2,6 times more likely to default than an anchor. Additionally, a non-limited company is approximately 1,3 times more likely to default than a limited company. While the status of a tenant can only very rarely change, it must be taken into account, that only good brands with a positive footfall effect, and thus with

good sales are considered anchors. This means the anchors are assumed not to default.

Opposite to OCR difference, increase in monthly sales per GLA decrease the probablility of default. However, by applying the equation 11 with a decrease of 500 euros per square meter in monthly sales, the probability of default multiplies by only 1,15 times. The sales decrease of 500 €/sqm itself is quite large, and with the total probability increasing only by 1,15-fold, the effect of monthly sales is not very large. This is also somewhat expected, as OCR, and therefore the costs as well as turnover, is thought to have a much larger impact on the tenant's ability to pay.

Credit ratings themselves are the most significant independent variable of the model, and it can also change for a tenant from time to time. Table 14 represents the odds ratios for all possible credit ratings, along with the significance of the odds ratio (*P*-values). In the table, the odds ratio is the ratio of default probability of Level1 over default probability of Level2. Thus, the odds ratio describes how many times more likely is a default, when a company's credit rating changes from Level2 to Level1, given that all other factors remain unchanged. For example, a change from a rating of at least A to a C increases the odds of default 28-fold. It can be seen that the change from No rating to B (or the other way round) does not affect the probability much and is not statistically significant.

Table 14. Odds ratios for credit rating changes (SAS JMP).

Level1	**/Level2**	**Odds Ratio**	**P-value**
> A	-	0,239023	0,0321*
> A	B	0,2265358	0,0044*
> A	C	0,0356164	<,0001*
B	> A	4,4143124	0,0044*
B	-	1,0551221	0,9419
B	C	0,157222	0,0006*
C	> A	28,076937	<,0001*
C	-	6,711033	0,0073*
C	B	6,3604327	0,0006*
-	> A	4,1836982	0,0321*
-	B	0,9477576	0,9419
-	C	0,1490084	0,0073*

As mentioned previously, the differences between the effect of sales categories seem extremely large. Especially the coefficient for groceries and other commercial services is so low, that it is practically impossible to estimate the default probability of those sales categories. However, this is due to most groceries and other commercial service tenants being very large national or international chains with high credit ratings and well known brands, and them not defaulting in the input data. On the other hand, department stores are the most likely to default, according to the model. The fact there is no defaults creates a bias towards not defaulting, as the sample sizes for both sales categories is large enough for the model fitting to assume they can't default. In practice this will be taken into account by following the other independent variables, i.e. sales, OCR, and credit rating, and especially the radical and long term changes in them.

6 APPLYING THE LOGISTIC MODEL FOR SHOPPING CENTER MANAGEMENT

The logistic regression model presented in chapter 5.3 can be a helpful tool for shopping center managers and for financial professionals in recognizing tenants with a high risk of default, as well as to follow the development of tenants considered risky. The information needed for the model is easily attainable and mostly real time. The tenants report their sales monthly, only a few days after the month's end, meaning sales per GLA and OCR can be calculated instantly, and therefore reacted to, before collaterals need to be monetized or the tenant put into debt collection.

6.1 Challenges of the logistic model

The main challenge with the model is the way credit rating is estimated. The rating itself can be checked any time, but there will always be a delay before the rating is updated. This causes the credit rating to indicate a past condition of the company, while the purpose of the model is prediction. Additionally, there can be slight inconsistency in the credit ratings. This can be seen in a credit rating change report by Bisnode, in which the rating of some companies changes back and forth within a few days. If the credit rating report is exported in the middle of this kind of period, the rating would not necessarily be accurate. Fortunately, these events are rare, and the inconsistencies can easily be tracked.

Even though the credit rating indicates the past, in some cases it can still help analyze the tenants. For example, some tenants might pay rent normally, but default on other obligations. This can be even likely with tenants that sell services, rather than products, as defaulting on purchases could lead to not being able to sell anything. In addition, the premises can be the most important factor in selling services in addition to employees. Additionally, a tenant that is doing well in the shopping center could have business elsewhere, that is going bad. This can lead to

surprising bankruptcies with the tenant having good sales in the shopping center while struggling outside it. Thus, a negative credit rating change can be a useful early warning for most tenants.

Another questonable result in the logistic model is the high effect some sales categories have on the default probability. However, the main purpose of the model is to help detect struggling tenants, and the ones, whose financial capability is progressing negatively. Thus, it is adviced to observe the changing variables, such as credit rating, OCR, and sales per GLA.

6.2 Recognizing high risk tenants

High risk tenants must be recognized in two phase: leasing and continuous monitoring. In leasing, it is important to either not offer a lease agreement to a potential tenant whose default risk is high, or to take the risk into account with shorter lease term and rent premium. Either way, it is beneficial to find a tenant with a low default risk, because the high risk tenant can more easily cause credit losses and re-letting costs with default and potential early termination. Continuous monitoring is for shopping center management to observe the development of their tenants and to intervene with struggling tenants to either help them survive or minimize the damages for the center.

In the leasing phase, especially with new tenants, sales numbers are not available. This leads to the situation in which the default risk must be evaluated only with credit rating and constant variables. The logistic model can be applied to this scenario, by estimating the OCR to be the sales category average and the average monthly sales close to comparable tenants' average. Thus the credit rating, sales category, and company type (and anchor status in some cases) have the largest effect on the default probability. As a general rule of thumb, potential tenants with credit rating C should not be considered, and potential tenants with credit rating B or no rating should only be considered if their other favorable attributes.

For the shopping center management, it is more worthwile to observe the development of the tenants with the changing variables. While the logistic model itself is a decent indicator for default probability, it can be used as a tool to help easily recognize the development of certain high risk tenants. Especially decreasing sales and negative credit rating changes, along with increasing receivables and delays in rental payments are strong indicators of a tenant, whose probability of default radically increases. The shopping center management should thus communicate with these tenants to find the root of the problem, and either help them survive a temporary problem with e.g. rental discounts, or exercise debt collection and if possible, get rid of the bad tenant. Also the fact that the case company requires a collateral from nearly all tenants increases the time to react to a tenant's negative development, as the collateral covers up to four months' rent.

As is with all risk management, risk must be combined with effect. This can practically be seen in shopping centers with struggling anchors, where the loss of an anchor significantly decreases the center's income (Gatzlaff et al. 1994). Thus, it is important for the shopping center management to be the most critical towards large tenants, as their impact on the whole center's economy can be large either directly by high rent, or indirectly by creating footfall.

7 Conclusions

There are a large number of factors affecting the shopping center industry, including trends, regulation, and overall economy. Individual shopping centers in addition are affected by the center's location and thus the catchment area and accessibility, and the success of its tenants. The tenants ultimately make the shopping center attractive and create footfall, and the benefit should be maximized with the most optimal tenant mix, while taking into account the development of the whole industry.

To achieve the best possible tenant mix includes finding the most attractive tenants with wide enough array of sales categories for the right locations, and maybe most importantly, determine the correct rent for each tenant. To determine the right rental level includes analyzing the tenant's attributes, as well as the center's. While it would be the most beneficial for the center to aim for as high rent as possible, it can cause defaults and vacancy, and therefore financial disadvantage for the center, along with the center becoming less attractive. Thus, a sustainable rental level is important for all parties.

The risk of default is the main risk a shopping center carries for its tenants, due to the reliability of the cash flow being a large factor in the success and value of the shopping center. Thus, the financial sustainability of tenants is extremely important for the whole center, and it can be measured with occupancy cost ratio. It is noticed, that OCR is not widely studied, and there doesn't seem to be an agreed sustainable OCR level in literature, especially between different sales categories.

Another way to measure the reliability of a tenant is its credit rating. Credit rating is usually automatically calculated by rating companies, while taking into account the estimated company's operation, background, finance, and ability to pay. Most companies in Finland are creditworthy, having a low probability of default, but companies with low credit rating (B or C) are very likely to default in a two year period.

The effect of credit risk in shopping centers can be minimized with collaterals, requiring the rent up front, or as the last option, debt collection. All these methods are used in the case company, with collaterals being the most used and effective way to reduce the financial risk. However, to reduce the overall default risk, would be to recognize the preferred tenants with low risk as early as in the leasing phase.

7.1 Findings

In addition to the literature, multiple logistic regression based on case company data, as well as credit rating data from Bisnode, was used in this thesis to find answers to the research questions:

1. What kind of tenants default their obligations?
2. Which factors affect the ability to pay rent?
3. Can defaults be prevented?

The most likely tenant to default can be concluded from the final logistic model, and it has a credit rating C, along with low sales and high OCR. A bad credit rating clearly indicates a high risk tenant, which is expected, considering this is also supported by multiple studies (e.g. Hutchison et al. 2008; Lopez & Saidenberg, 2000; Renigier-Bilozor et al. 2017).

The static attributes of the tenant are not as crucial for the default probability, but it can be seen that some sales categories have higher tendency to default. These riskier categories are department stores, cafes and restaurants, and home supplies and furniture. Of the riskiest sales categories, departments stores can be seen as a casualty of the e-commerce trend, as most items sold in them can be bought online. On the other hand, the least risky sales category, groceries are at least in Finland e-commerce safe and it seems they will be in the future. Some grocery delivery and collecting services are already available, showing the ability to adapt to new trends, which Achenbaum (1999) and International Council of Shopping Centers (2015) consider vital.

The factors with the largest effect on the tenant's ability to pay rent can also be concluded with the logistic model. As seen in the literature, the logistic model shows high OCR to weaken the ability to pay rent. This is also linked to the average sales per GLA, which in a different way shows the tenant's performance. In addition, credit rating has a massive effect on the ability to pay rent, as it's a comprehensive indicator of the company's financial situtation. However, the problem with credit rating is its nature as a look into the past, but it can be overcome in the cases a tenant hasn't shown signs of negative development in the shopping center, but its credit rating still drops, indicating the situation might spread into the center. Other factors affecting the ability to pay rent are wether the tenant is an anchor, a limited company, and in which sales category its business belongs to. The difference in default probability between anchor and non-anchor, and between limited and non-limited company isn't necessarily large, but the regression analysis does indicate anchors and limited companies to be more reliable. Additionally, the proposition of Hutchison et al. (2008) that the risk profile of limited companies is lower than non-limited companies, is supported by this research. Sales categories have large differences in default probabilities due to the different cost structures and natures of business.

Overall defaults in shopping centers can be prevented with constant monitoring of all tenants to recognize tenants with high or growing risk of default. This can be done with monthly sales figures and periodic credit rating checks, and applying the logistic regression model presented in this thesis into the monitoring, and estimating the default probability for each tenant. Alternatively, the monitoring can be made for only the changing variables, and taking note of tenants with decreasing sales and negatively changing credit ratings. Additionally, the model can be used in leasing, to help recognize financially unstable companies with high default probability, making the tenant mix higher quality from the start.

The model can also be combined with information about receivables and payment delay to help the shopping center management recognize the tenants who show

signs of weak financial ability. This is supported by the research by Lamy (2000), which indicates erratic payment trends a way to noticehigh risk tenants. Also, the shopping center management should study market trends to recognize possible market risks caused by them. New trends will always alter the optimal tenant mix, and should be implemented into the risk model, as different sales categories might turn out to be very different by their risk profile in a few years time.

As is with all risk management, the effect of an action must be taken into account. This means the shopping center management must prioritize the largest struggling tenants when needed, as their default and in the worst case, them leaving could have a massive negative effect on the center. In the case company, most tenants have collaterals in place to minimize the financial effect of defaults and damages, offering a little more time for the management to react.

7.2 Future research

An obvious future research subject would be the sustainable OCR levels. As they have not been studied intensively, especially taking into account the different sales categories, category averages had to be used in this thesis as the benchmarks. Thus, the connection between default and OCR within different sales categories could be more evident. Further, the factors affecting the sustainable OCR level, e.g. cost structure, should be studied, while keeping the differences of the sales categories as focus points.

Additionally, the sales categories in this thesis are divided similarly as the Finnish Council of Shopping Centers does. This may not be the best categorization, as there are large differences in businesses within the categories, e.g. sales category leisure includes entertainment, such as cinemas, as well as sporting retailers. Thus, a study to perhaps reorganize the sales categories would be needed in order to harmonize them.

REFERENCES

Achenbaum, A. A. 1999. Retail stores, not e-commerce, will dominate. *Marketing Management.* Vol. 8, no. 4, pp. 64.

Ambrose, B.W. & Yildirim, Y. 2008, Credit Risk and the Term Structure of Lease Rates: A Reduced Form Approach. *Journal of Real Estate Finance and Economics. V*ol. 37, no. 3, pp. 281-298.

Ardill, R. 2006. Future of Retail Property: Future of Brands. Report 4. London, British Council of Shopping Centres. 60 p.

Benjamin, J., Boyle, G. & Sirmans, C.F. 1992. Price discrimination in shopping center leases. *Journal of Urban Economics.* Vol. 32, no. 3, pp. 299-317.

Berry, K., Mielke, P. & Johnston, J. 2016. Permutation Statistical Methods. Cham, Springer International Publishing. 622 p.

Bisnode. 2017a. Credit rating statistics in Finland. [online]. [accessed 21.7.2017]. Available: https://www.bisnode.com/suomi/juuri-nyt/tilastot/rating-tilastot/

Bisnode. 2017b. Rating-model. [online]. [accessed 28.7.2017]. Available: https://www.bisnode.com/suomi/juuri-nyt/yleista-tietoa/aaa-rating-malli-ja-luokat/

Calanog, V. & Marsh, S. 2009. Managing Risk in Retail Property Lending. *The RMA Journal.* Vol. 92, no. 1, pp. 12-18.

Carter, C. C. 2009. What We Know About Shopping Centers. *Journal of Real Estate Literature*. Vol. 17, no. 2, pp. 165-180.

Cho, H. & Shilling, J.D. 2007. Valuing Retail Shopping Center Lease Contracts. *Real Estate Economics.* Vol. 35, no. 4, pp. 623-649.

Cope, C. R. 1999. CHAPTER 4: Tenant Mix and Leasing Strategies, in *Shopping Center Management*, International Council of Shopping Centers, pp. 73-95.

Daniels, A. & McDonnell, P. 2003. A Guide to Occupancy Costs. *Retail Traffic.* Vol. 32, no. 5, pp. 214-215.

Dawson, J. & Lord, D. (eds.) 2012. Shopping Centre Development (RLE Retailing and Distribution). New York, Routledge. 288 p.

Des Rosiers, F., Thériault, M. & Lavoie, C. 2009. Retail Concentration and Shopping Center Rents: A Comparison of Two Cities. *Journal of Real Estate Research.* Vol. 31, no. 2, pp. 165-207.

Edmund, T., McKenzie, F., Warren, S., Glickman, B. & Elphick, J. 2012. The ups and downs of rent review. *The Estates Gazette*. pp. 112-113.

El-Adly, M. I. 2007. Shopping malls attractiveness: A segmentation approach. *International Journal of Retail & Distribution Management.* Vol. 35, no. 11, pp. 936-950.

Finnish Council of Shopping Centers. 1997. Shopping center lease appendix. [online]. [accessed 30.7.2017]. Available: http://www.kauppakeskusyhdistys.fi/attachements/2005-09-29T16-34-4340.htm

Finnish Council of Shopping Centers. 2010. Finnish Shopping Centers 2010. [online]. [accessed 18.7.2017]. Available: http://www.kauppakeskusyhdistys.fi/attachements/2010-04-15T12-53-4265.pdf

Finnish Council of Shopping Centers. 2017. Finnish Shopping Centers 2017. [online]. [accessed 18.7.2017]. Available: http://www.kauppakeskusyhdistys.fi/attachements/2017-04-06T08-12-3186.pdf

Gatzlaff, D., Sirmans, S. & Diskin, B. 1994. The Effect of Anchor Tenant Loss on Shopping Center Rents. *The Journal of Real Estate Research.* Vol. 9, no. 1, pp. 99-110.

Giannotti, C. & Mattarocci, G. 2008. Risk diversification in a real estate portfolio: evidence from the Italian market. *Journal of European Real Estate Research*. Vol. 1, no. 3, pp. 214-234.

Giesecke, K. & Kim, B. 2011. Systemic Risk: What Defaults Are Telling Us. *Management Science*. Vol. 57, no. 8, pp. 1387-1405.

Goedken, A. K. 2006. The Shopping Center's Future. *Buildings.* Vol. 100, no. 11, pp. 80-82.

Gould, E., Pashigian, B. & Prendergast, C. 2005. Contracts, Externalities, and Incentives in Shopping Malls. *Review of Economics & Statistics*. Vol. 87, no. 3, pp. 411-422.

Graham, J. & Harvey, C. 2001. The theory and practice of corporate finance: evidence from the field. *Journal of Financial Economics.* Vol. 60, no. 2-3, pp. 187-243.

Grenadier, S. 1996. Leasing and credit risk. *Journal of Financial Economics.* Vol. 42, no. 3, pp. 333-364.

Hofmann, S. 2015. How to evaluate the performance of a shopping center investment. [online]. [accessed 30.7.2017]. Available: https://www.across-magazine.com/kpi-key-performance-indicators/

Hutchison, N., Adair, A. & Findlay, N. 2009. The Treatment of Covenant strength by the UK Property Industry. Investment Property Forum. [online]. [accessed

19.7.2017]. Available: http://www.ipf.org.uk/asset/9BC4F370-6DBB-46DF-9AEC84A1522BFC17/

Hutchison, N., Adair, A. & McWilliam, J. 2008. Covenant strength in shopping centres: a diversified risk?. *Journal of Property Investment & Finance*. Vol. 26, no. 4, pp. 329-341.

Hutchison, N., Adair, A. & Park, K. 2010. The value of rental deposits. *Journal of Property Investment & Finance.* Vol. 28, no. 4, pp. 250-262.

International Council of Shopping Centers. 2005. ICSC Dictionary of Shopping Center Terms. New York, ICSC.

International Council of Shopping Centers. 2015. Exploring new leasing models in an omni-channel world. New York: International Council of Shopping Centers.

International Council of Shopping Centers. 2016. Nordic Retail Market Analysis. [online]. [accessed 19.7.2017]. Available: http://www.icsc.org/research/publications/downloads/ICSC_NCSC_Nordic-Retail-Market-Analysis-Final.pdf

International Council of Shopping Centers. 2017. The Successful Integration of Food & Beverage Within Retail Real Estate. [online]. [accessed 19.7.2017]. Available: https://www.icsc.org/uploads/research/general/Food_Beverage_Study_UK.pdf

Investment Property Forum. 2015. Individual Property Risk. [online]. [accessed 20.7.2017]. Available: http://www.ipf.org.uk/asset/DD055D34-721A-4B8E-95CD2A7CECBC4B20/

Jarrow, R., Lando, D. & Turnbull, S. 1997. A Markov model for the term structure of credit risk spreads. *Review of Financial Studies.* Vol. 10, no. 2, pp. 481-523.

Kleinbaum, D. & Klein, M. 2010. Logistic Regression. 3rd edition. New York, Springer Science+Business Media. 701 p.

Lamy, K. 2000. CHAPTER 7: Using Numbers to Manage Your Business. *Finance for Shopping Center Nonfinancial Professionals*. International Council of Shopping Centers, pp. 139-163.

Lopez, J. & Saidenberg, M. 2000. Evaluating credit risk models. *Journal of Banking & Finance.* Vol. 24, no. 1, pp. 151-165.

Lowe, M. 2005. The regional shopping centre in the inner city: A study of retail-led urban regeneration. *Urban Studies (Routledge).* Vol. 42, no. 3, pp. 449-470.

McFadden, D. 1974. Conditional logit analysis of qualitative choice behavior. In *Zarembka, P. (Ed.) Frontiers in econometrics*. New York, Academic Press, pp. 105-142.

Miceli, T., Sirmans, C. & Turnbull, G. 2009. Lease defaults and the efficient mitigation of damages. *Journal of Regional Science*. Vol. 49, no. 5, pp. 915-930.

Myers, H., Gore, J. & Liu, K. 2008. European shopping centre developments: an industry perspective. *Journal of Place Management and Development.* Vol. 1, no. 1, pp. 109-114.

Peng, C., Lee, K. & Ingersoll, G. 2002. An Introduction to Logistic Regression Analysis and Reporting. *The Journal of Educational Research*. Vol. 96, no. 1, pp. 3-14.

Phelan, J. 2000. CHAPTER 5: Retail Leasing. *Finance for Shopping Center Nonfinancial Professionals*. International Council of Shopping Centers, pp. 85-101.

Raslanas, S. & Lukošienė, I. 2013. The determination of rents in shopping centers during recession period in Lithuania. *International Journal of Strategic Property Management.* Vol. 17, no. 3, pp. 221-232.

Renigier-Bilozor, M., Wisniewski, R. & Bilozor, A. 2017. Rating attributes toolkit for the residential property market. *International Journal of Strategic Property Management.* Vol. 21, no. 3, pp. 307-317.

Schmit, M. 2004. Credit risk in the leasing industry. *Journal of Banking & Finance*. Vol. 28, no. 4, pp. 811-833.

Sing, T. F. & Tang, W. L. 2004. Valuing leasing risks in commercial property with a discrete-time binomial tree option model. *Journal of Property Investment & Finance.* Vol. 22, no. 2, pp. 173-191.

Sirmans, C. & Guidry, K. 1993. The Determinants of Shopping Center Rents. *Journal of Real Estate Research.* Vol. 8, no. 1, pp. 107-115.

Sit, J., Merrilees, B. & Birch, D. 2003. Entertainment seeking shopping centre patrons: The missing segments. *International Journal of Retail & Distribution Management*. Vol. 31, no. 2, pp. 80-94.

Smith, G. 2009. More Than Just Shuffling the Pack: The Changing Face of Retail Industries in a Recession (Part 1 of 2). *The RMA Journal.* Vol. 91, no. 7, pp. 26-31.

Sung, M., McDonald, D. & Johnson, J. 2016. Probabilistic forecasting with discrete choice models: Evaluating predictions with pseudo-coefficients of determination. *European Journal of Operational Research.* Vol. 248, no. 3, pp. 1021-1030.

Tay, R., Lau, C. & Leung, M. 1999. The Determination of Rent in Shopping Centers: Some Evidence from Hong Kong. *Journal of Real Estate Literature.* Vol. 7, no. 2, pp. 183-196.

Wheaton, W. 2000. Percentage Rent in Retail Leasing: The Alignment of Landlord-Tenant Interests. *Real Estate Economics.* Vol. 28, no. 2, pp. 185-204.

White, J.R. & Gray K.D. 1996. Shopping Centers and Other Retail Properties. New York, John Wiley & Sons, Inc. 512 p.

World Bank. 2017. GDP per capita statistics. [online]. [accessed 1.11.2017]. Available: https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG?end=2016&locations=FI-SE-NO&start=2008&view=chart

Wyatt, P. 2013. Property Valuation. Chichester, John Wiley & Sons, 496 p.

Yap, B.W., Ong, S.H. & Husain, N.H.M. 2011. Using data mining to improve assessment of credit worthiness via credit scoring models. *Expert Systems with Applications.* Vol. 38, no. 10, pp. 13274-13283.

Yiu, C. & Xu, S. 2012. A tenant-mix model for shopping malls. *European Journal of Marketing.* Vol. 46, no. 3, pp. 524-541.

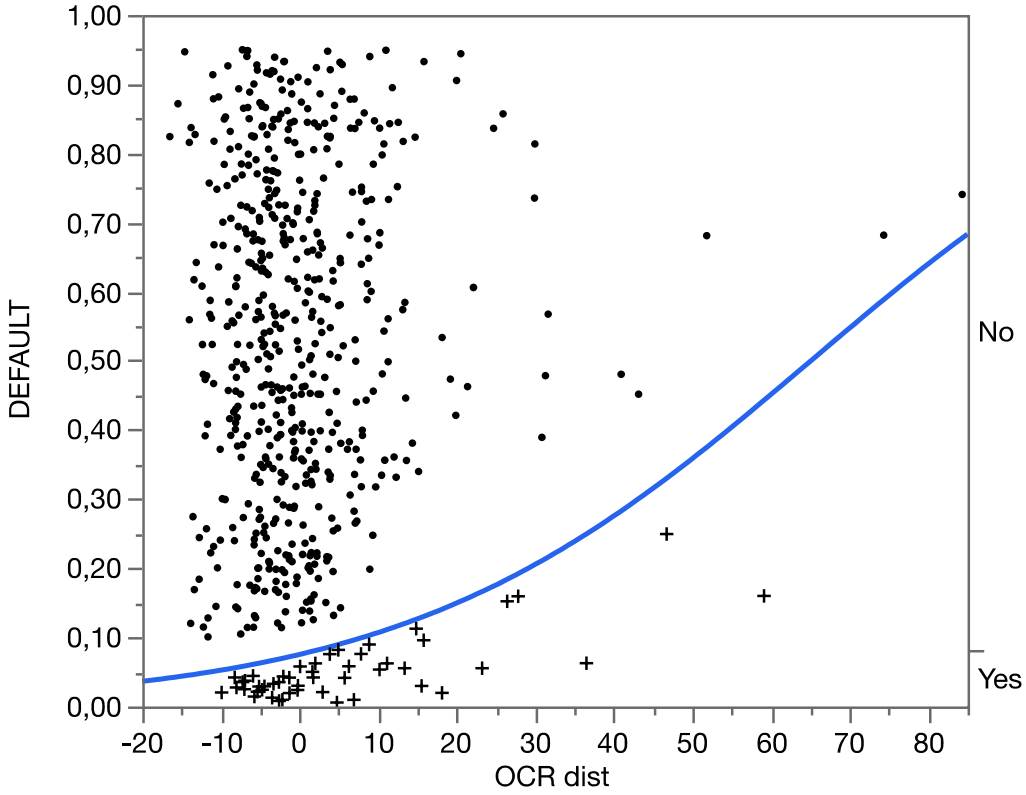
Appendix 1: Contingency analysis of default by limited credit rating

	DEFAULT		
Count Row %	Yes	No	Total
AAA	2 2,86	68 97,14	70
AA	7 3,45	196 96,55	203
A	5 2,72	179 97,28	184
Total	14	443	457

N	DF	-LogLike	RSquare (U)
457	2	0,09235018	0,0015

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	0,185	0,9118

Appendix 2: Logistic fit of default by OCR distance



Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	5,78362	1	11,56724	0,0007*
Full	161,22720			
Reduced	167,01082			

RSquare (U)	0,0346
AICc	326,475
BIC	335,238
Observations (or Sum Wgts)	597

Appendix 3: Contingency analysis of default by anchor

Anchor	DEFAULT		
Count Row %	Yes	No	Total
0	46 9,48	439 90,52	485
1	2 1,79	110 98,21	112
Total	48	549	597

N	DF	-LogLike	RSquare (U)
597	1	4,8786193	0,0292

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	9,757	0,0018*

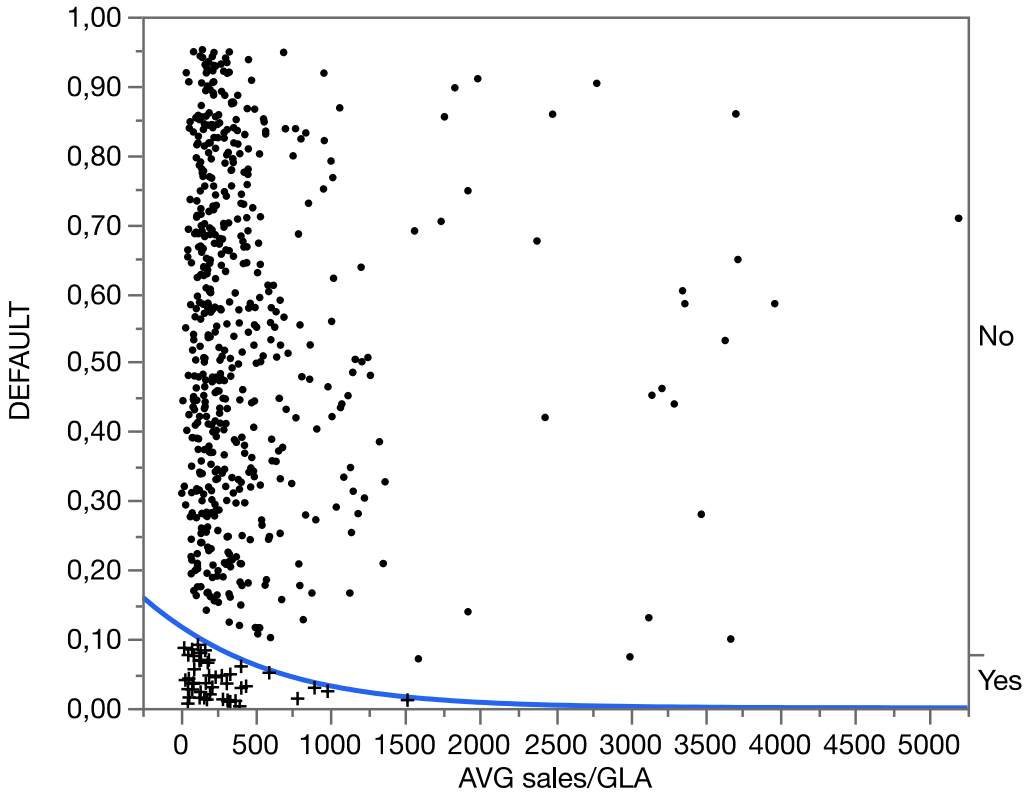
Appendix 4: Contingency analysis of default by company type

Company type	Count Row %	DEFAULT Yes	No	Total
	Limited	35	473	508
		6,89	93,11	
	Other	13	76	89
		14,61	85,39	
	Total	48	549	597

N	DF	-LogLike	RSquare (U)
597	1	2,6069879	0,0156

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	5,214	0,0224*

Appendix 5: Logistic fit of default by average sales per GLA



Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	3,84596	1	7,691929	0,0055*
Full	157,51780			
Reduced	161,36377			

RSquare (U)	0,0238
AICc	319,056
BIC	327,789
Observations (or Sum Wgts)	588

Appendix 6: Contingency analysis of default by credit rating

Credit rating	DEFAULT		
Count Row %	Yes	No	Total
> A	14 3,06	443 96,94	457
-	5 14,71	29 85,29	34
B	7 11,48	54 88,52	61
C	22 48,89	23 51,11	45
Total	48	549	597

N	DF	-LogLike	RSquare (U)
597	3	37,313928	0,2234

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	74,628	<,0001*

Appendix 7: Contingency analysis of default by sales category

Sales category	DEFAULT		
Count Row %	Yes	No	Total
Cafes and Restaurants	12 11,88	89 88,12	101
Department Stores	1 8,33	11 91,67	12
Fashion	12 8,82	124 91,18	136
Groceries	0 0,00	53 100,00	53
Health and Beauty	10 9,71	93 90,29	103
Home	4 11,11	32 88,89	36
Leisure	8 7,77	95 92,23	103
Other commercial services	0 0,00	21 100,00	21
Specialty retailers	1 3,13	31 96,88	32
Total	48	549	597

N	DF	-LogLike	RSquare (U)
597	8	8,2112342	0,0492

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	16,422	0,0367*