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Fintech in Credit Rating Agencies: Evolutionary or Revolutionary?

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INTRODUCTION

The popularity of Credit Rating Agencies (CRAs) has been increasing since the global financial crises. Today, CRAs became even more crucial in the global financial market since their judgment has a significant impact on a country, its financial players and even the individuals.

Together with the ongoing developments of technological innovations, technological integration became vital in almost every sector but even more for financial institutions. In today's world, FinTech became a very important technology because not only having an effect on financial institutions' operations but also on individuals' daily life. Moreover, FinTech drives and encourages financial institutions to change and differentiate the way of providing their services. As a result, Fintech has grown and been growing rapidly day by day.

However, even though these technologies seem helping to improve innovative services of financial institutions, for those who cannot integrate these technologies into their businesses may face many challenges and may end up even with a bankruptcy. Therefore, question of "how financial institutions will be affected by FinTech" became the main concern and concept that needs to be investigated.

In this thesis, the primary focus is to explore the impact of FinTech on CRAs. Therefore, this thesis will conduct an exploratory study in order to contribute to the existing information about the potential impact of FinTech on CRAs. Accordingly, this study aimed to answer the research question within the scope of qualitative methodology and using the empirical data has been gathered from the professionals in the finance through the combination of survey and semi-structured interviews.

Keywords: [Credit Rating Agencies (CRAs), FinTech, exploratory study, qualitative method]

CHAPTER 1: CREDIT RATING AGENCIES

Chapter 1 reviews the theoretical background of Credit Rating Agencies. This chapter starts with the birth of CRAs, continues with the introduction of CRAs and its rating, followed by insight of their traditional rating methodologies and the overview of biggest rating agencies. Moreover, this chapter will look CRAs' evaluation and the process of how they became so vital in today's world through as a result of the main historical events. Finally, Chapter 1 will be concluded with an overview of the effects of credit rating agencies.

1.1 The Rise of CRAs

A credit rating agency is an independent organization which specialized of analyzing and assessing the creditworthiness of corporates and sovereign issuers of debt securities (Elkhoury, 2018).

The main concern of any lender is how likely will any potential borrower repay the loan. To minimize these concerns, the lender seeks an outside guidance aside from the information on potential borrowers, collaterals or strict agreements that minimize the risk of uncollectibility (White, 2010). At this point, a credit rating agency steps in and enlightens the lender about the risk with the ratings that represent judgements as they called "opinions". This form of opinion first emerged in 1909 in the form of a bond rating. Of course, the bond ratings did not just come naturally within capital market. Actually, capital market has much older history than the invention of bond ratings. Before the first agency rating, Dutch investors were buying bonds for 300 years while English was 200 and American was 100 (Sylla, 2002). So, what happened then, and how credit rating agencies became a part of the capital market?

In the beginning of the nineteenth century the international bond market, mostly in sovereign debts, grew rapidly and the relationship between the investors and the issuers was mainly built on trust. Moreover, the capital needs of business in Europe were mostly met through bank borrowings and equity issues. However, by 1850, the way of meeting the capital needs of businesses in the United States differentiated due to having a different economic structure than Europe. US economy was continental-size, whereas its development projects and its individual enterprises were large scales. Between the years of 1817 and 1840s, many states in the US issued bonds to finance projects such as building canals and infrastructure projects. However, these projects largely were dropped off following the nine states defaulted on these debts beginning of the 1840s (Sylla, 2002). The country's most prominent project was to connect itself from end to end. Railroads companies were mostly private and raised the necessary capital for this project through bank loans and stock issues. However, together with the increased volume in trade stemming from building canals and railroads, merchants started to trade with outside customers and towns which they did not know personally. Moreover, due to the insufficiency of having credit information, and the rapid change in financial conditions of businessman, resulted a need of up-to-date information for wholesalers and other investors. As a result of this need in 1841, the Mercantile Agency was established to provide reports about creditworthiness of the business, followed by another agency called the Bradstreet Agency in 1849 (Madison, 1974). Meanwhile investors were not only using these agencies' reports but also using the reports from journals to be informed about railroad business. The American Railroad Journal, which was established in 1832, was one of the first specialized publication. Henry Varnum Poor became its editor in 1849, concomitantly the publications altered being an investor-oriented in railroad business (Langohr & Langohr , 2008). In 1968, he published Poor's Manual of the Railroads of the United States, which contained a comprehensive report on railroad's financial and operating statistics as well as comparative information on companies' assets and earning powers (Sylla, 2002).

America's railroad corporations became one of the biggest and popular business in the world. Starting from year of 1850, railroads companies advanced their operations further, as their capital needs. They broaden to the territories to undeveloped "the wild west" where banks and investors willing to invest were scarce. In the end, the solution to raise capital was to develop a massive market in railroad company bonded debt rapidly. Together with this innovative development, by the early 1890s, the American railroad company bond market became much larger than the bond markets of Dutch, English or US (Rudden, 2020).

The agency ratings did not just appear out of thin air, but occurred in the course of the time, and developed from the mixture of three important institutions: credit reporting agencies which mentioned earlier such as The Mercantile Agency, specialized financial press, Poor's Manual of the Railroads, and lastly investment bankers. Investment bankers acted as financial intermediaries to distribute the securities in railroad businesses by putting their reputations between the transactions. They had access to inside and privileged information playing an active role in order to monitor the companies and securities deeply. However, at some point, these institutions became insufficient to certificate the creditworthiness and quality of the borrowers due to the rapid growth in issues and issuers (Sylla, 2002). As a result of a combination of these three institutions, the first rating was given by Moody's on railroad bonds in 1909, after that by Poor's Publishing Company followed in 1916. In 1922 Standard Statistics Company published its first rating, followed by the Fitch Publishing Company in 1924. These firms evolved over time: Dun & Bradstreet bought Moody's in 1962 but then subsequently spun it off in 2000 as a free-standing corporation. Poor's and Standard merged in 1941; Standard & Poor's was then absorbed by McGraw- Hill in 1966. Fitch merged with IBCA (a British firm, a subsidiary of FIMILAC, a French business services conglomerate) in 1997. At the end of the year of 2000, at about the time that structured securities market that was based on subprime mortgages for residential started to grow rapidly, the issuers of these securities had only these three credit-rating agencies to whom they could turn to obtain their all-important ratings: Moody's, Standard & Poor's (S&P), and Fitch. (White, 2010)

1.2 Credit Rating Agencies and Their Ratings

There are three main ways for those who consider lending money; either they collect the information about borrowers' ability to repay their debts on their own or look for outside advice or even both. In all ways, the primary purpose is to collect as much information as possible. In this matter, Credit Rating Agencies (CRAs) step in. The primary purpose here is to help to eliminate asymmetric information by offering judgements, agencies prefer calling opinions, about the bond credit quality and exposing as the hidden information as possible (White, 2010). CRAs are the institutions that designate credit risk to issuers such as banks, corporations and countries by gathering information about their creditworthiness. (Roberts, 2008). Consequently, the investor will have an opinion or perspective to decide if the issuer is reliable and worth contributing money against its assigned credit risk.

Credit Rating Agencies represent their opinions on the relative credit strength of issuers or issues through ratings (Langohr & Langohr , 2008). Although there is no standard scale for every CRAs, they mostly use letters to express their evaluation and all rating scales are comparable. *Figure 1* shows rating scales for the three biggest credit rating agencies (Fitch, Moody’s and S&P) and their comparisons. The ratings start with the highest “AAA” while ends with the lowest “D” in S&P and Fitch cases and “C” in Moody’s. These ratings can be assigned to short-term and long-term institutions’ debt obligations. Nevertheless, long-term credit ratings tend to be more indicative as a general measure of creditworthiness for investors, creditors or other related parties. The instrument rated AAA represents the meaning of lowest default risk expectation while D and C are the highest. Accordingly, BB rated instruments are more likely to default than A rated ones, but more likely to default than CC. However, these indexes neither tell how much more or how much less likely to default between the ratings nor define the exact default probability of rated instruments (Langohr & Langohr , 2008).

Figure 1: Rating Comparison

	Moody's LONG TERM	Moody's SHORT TERM	Standard & Poor's LONG TERM	Standard & Poor's SHORT TERM	Fitch Ratings LONG TERM	Fitch Ratings SHORT TERM	Ability to Honor Financial Obligation
INVESTMENT GRADE	Aaa	P-1	AAA	A-1+	AAA	F1+	Highest
	Aa1		AA+		AA+		Very High
	Aa2		AA		AA		
	Aa3		AA-		AA-		
	A1		A+	A-1	A+	F1	High
	A2		A		A		
	A3	P-2	A-	A-2	A-	F2	
	Baa1		BBB+		BBB+		Adequate
	Baa2	P-3	BBB	A-3	BBB	F3	
	Baa3		BBB-		BBB-		
SPECULATIVE GRADE	Ba1	NP	BB+	B	BB+	B	Depends on Economic
	Ba2		BB		BB		
	Ba3		BB-		BB-		
	B1		B+		B+		Low Level
	B2		B		B		
	B3		B-		B-		
	Caa1		CCC+	C	CCC	C	Default Possibility
DEFAULT GRADE	Caa2		CCC				High Default
	Caa3		CCC-				Very High Default
	Ca		CC				
			C				
	C		D	/	DDD	/	In Default
	/				DD		
	/				D		

Source: Reorganized from www.jcrer.com.tr

There are two crucial categories that have a broader perspective: "investment grade" and "speculation grade". Investment grades, Baa3/BBB-/BBB- and higher, are important for certain borrowers in order to have complete market access as some of the investors are not allowed to invest in debt if the entity has a sub-investment grade. However, issues in the speculation grade category, Ba1/BB+/BB+ and lower, (aka non-investment, junk or high yield) are more prone to entail stronger operating and financial restrictions so necessarily subject to higher pricing in order to compensate the higher risk of default (Symondson, 2015). Lastly, another important concept is the outlooks which can be positive, negative, stable or developing (uncertain about the rate movement). These outlooks signify the trajectory of the rating over time (Fitch Ratings, n.d.).

These ratings are assigned based on issuer's solvency, ability to fulfil its financial obligations entirely and timely manner, as well as its willingness about them. The issuers are not the only ones who can be rated; these ratings can also be assigned to the issuances to understand its credit's quality and default possibility. These ratings can be given by not only global rating agencies such as S&P, Moody's and Fitch, but also given by local CRAs. Every credit rating agency uses its own methods to assess an issuer's credibility and publish its opinion through a specific rating measure. This thesis will generally focus on the three biggest global credit rating agencies, S&P, Moody's and Fitch, as they dominated the industry. The credit rating market is highly concentrated market as a result of the economy of scale in the market since the high cost of collecting related data and its analysis results a potential barrier to the market competition (Host, Cvečić, & Zaninović, 2012).

1.3 Introduction of the Biggest Rating Agencies – The Big Three

As mentioned before, the first rating was given on railroad bonds by Moody's after by Poor's Publishing Company in 1916 and by the Standard Statistics Company in 1922 which together originate fundamental of S&P, lastly by the Fitch Publishing Company in 1924. These rating agencies back in time form today's biggest rating agencies, known as big three Credit Rating Agencies: Moody's, S&P and Fitch. These rating agencies have grown throughout the history, gained power, and now are significantly crucial in today's capital market. In this section first, these biggest three agencies will be introduced.

1.3.1 MOODY'S CORPORATION (MOODY'S)

The company's establishment began with the publication of *Moody's Manual of Industrial and Miscellaneous Securities* by the founder of the company, John Moody in 1900. (Moody's History: A Century of Market Leadership, n.d.) This publication was providing investors information about bonds and stocks of US companies by using their background and statistics.

In 1907, speculative and manipulative investment in United Copper by two individual investors, Augustus Heinze and Charles Morse, ended up with a stock market crash. The loss caused by these two investors was immense, leading people into the fear of not being able to withdraw their money. This apprehension led to a big panic run on a bank and spread very quickly. Trusts[1] and banks were out of cash due to the high demand of customers' request for withdrawals. The crash started in New York led to a nationwide shortage of money (Financial Crises, 2018). This hit many states and local banks hard as well as Moody's Company which bankrupted due to the inadequacy of its capital. After the panic of 1907, which lasted one year, John Moody found a way to return to financial market offering a different service, analysis of security values offering detailed, to the point judgments about their investment quality, rather than simple company information collection for its property, capitalization and management. Finally, he expressed these concise conclusions with letter rating symbols (Moody's History: A Century of Market Leadership, n.d.).

According to a report published by European Securities and Markets Authority (ESMA) in December 2020, Moody's has 33.12% market share in EU registered CRA in terms of annual turnover generated from credit rating activities.

1.3.2. STANDARDS & POOR'S GLOBAL RATING (S&P)

Henry Varnum Poor formed the foundation of today's S&P. The company issued its first credit rating by the name of Poor's Publishing Company, after the Moody's, in 1916. Even though the company issued its first rating after the Moody's, Poor's publishments laid the foundation of the first rating. Started with the *Poor's American Railroad Journal* in the 1850s following the book in 1860, *History of Railroads and Canals of the United States of America,* draw a clear picture and gave detailed information about American infrastructure to help investors (Sinclair, 2005).

In 1906, Standard Statistics Bureau was founded by Luther Lee Blake, giving the information on industrials through issuing cards (Poon, 2012). Later on the company was known as Standard Statistic Company and issued its first rating in 1922. Standard Statistic Company and Poor's Publishing Company merged in 1941 and formed Standards and Poor's (S&P). In 1966 McGraw-Hill acquired the company and S&P became a division of McGraw Hill Financial Corporation. In 2016 McGraw Hill Financial continued its operation with the name of S&P Global (Our History, n.d.).

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[1] Trusts are businesses or firms that has a depository, agent or trustee relationship with another individual or business.

As the end of 2020, S&P Global Rating has the biggest market share among the other CRAs with a 40.4% share according to the ESMA's report on December 2020.

1.3.3 FITCH RATINGS INC. (FITCH)

Another one of the biggest rating agencies is the Fitch Rating founded by John Knowles Fitch, an American Economist, in 1913 under the name of Fitch Publishing Company. In 1923, Fitch introduced a rating scale form, AAA to D, which is now the most used rating scale system. Fitch was recognized as a Nationally recognized statistical rating organization (NRSRO) in 1975 by SEC (Company History, n.d.).

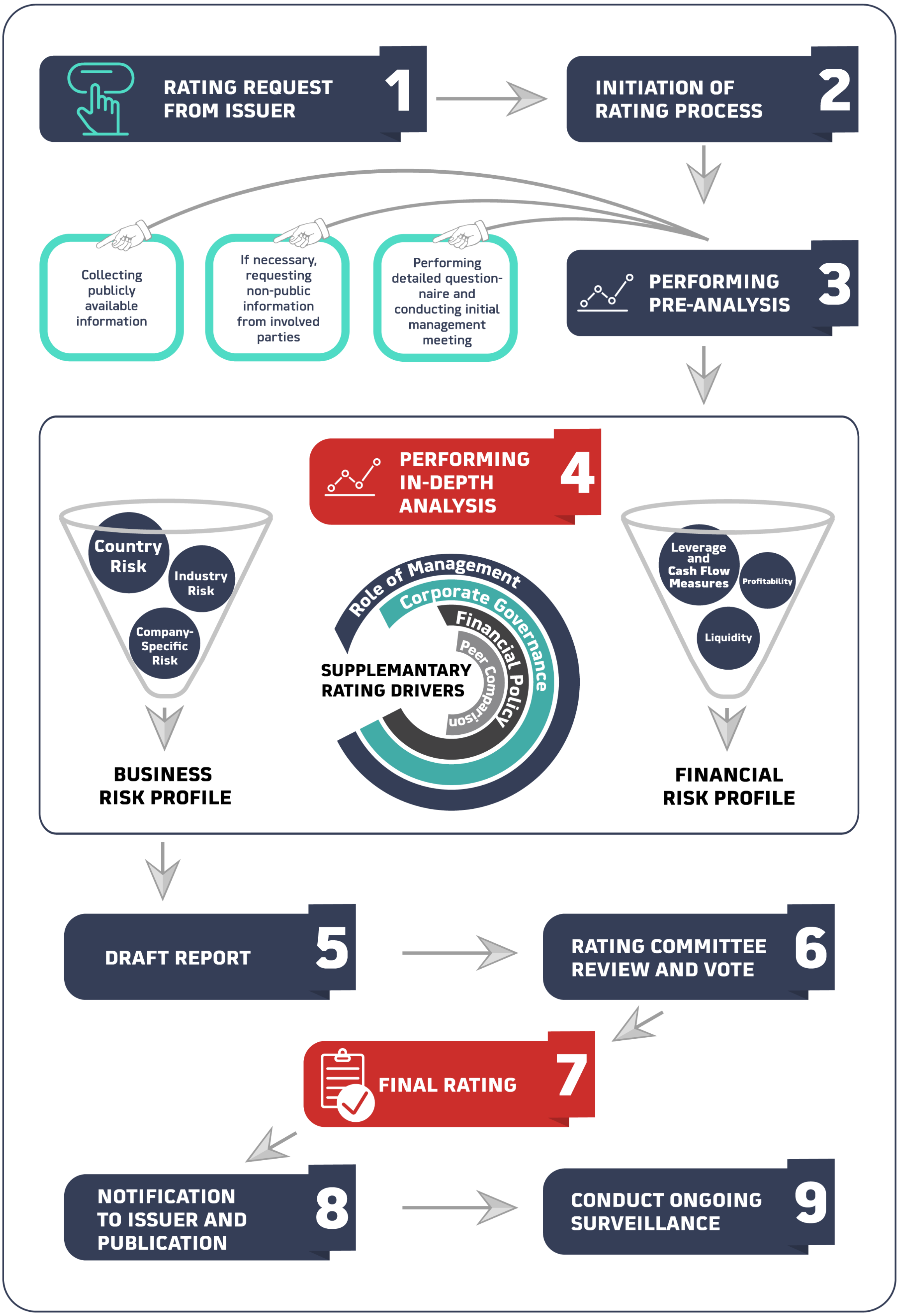
Fimalac SA, a holding company in Paris, acquired Fitch's Investors Services in October 1997 renamed as Fitch IBCA (LavinStaff, 1997). Fitch made an acquisition of Duff & Phelps Credit Rating Co., an NRSRO headquartered in Chicago, in April 2000 followed by another acquisition later that year of the rating business of Thomson BankWatch (Joynt, 2002). These acquisitions gave a growth momentum and strengthened its operation. Following these acquisitions, two years later the company launched its name as Fitch Ratings.

As the end of 2020, according to a report issued by ESMA, Fitch has 17.55% market share and continued its operation being the third-largest credit rating agency.

1.4 Traditional Rating Methodology of CRAs

The largest international credit rating agencies use generally similar procedures even though they operate independently and provide detailed methodology on their website. Fundamentally, the main approach achieving a final rate/opinion is to combine business and financial risk of the rated entity involved. (Symondson, 2015). Business risk comprises of the risk deriving from the country or industry in which the company operates as well as the company's position among its competitors (company-specific risk); while, financial risk refers to the company's financial position, its flexibility and ability to repay its obligations. Figure 2 provides the general view for credit rating process. After a rating request from an issuer, the rating process starts with the pre-analysis performance. Initially, in order to analyze the issuer, rating agency collect all the necessary publicly available information and, if it is necessary and applicable, they also request non-public information which is provided from directly issuer, sponsors or other involves parties (Fitch Ratings). A rating assessment is carried out by an

Figure 2: Credit Rating Process



Source: Own Elaboration

analyst in credit rating agency who works with the issuer client and his rating adviser-intermediary closely. Moreover, the agency conducts a detailed questionnaire and an initial meeting within the pre-analysis step. Following the three steps that can be seen in Figure 2, the analyst carries out in-depth analysis which are the evaluations of business risk, financial risk and the other risk factors of the issuer as mentioned earlier and will be explained in more detailed in the part 1.4.1 and 1.4.2. As a result of analyst's work, analyst proposes a rating to a rating committee which needs to be approved by. This committee is discretionary, and majority vote decides whether to confirm the rating or not. When the rating is approved, CRA informs the issuer, communicates with the market and conducts an ongoing control in case of change in rating (Langohr & Langohr , 2008). By default, this thesis will describe the corporate rating process and its methodology.

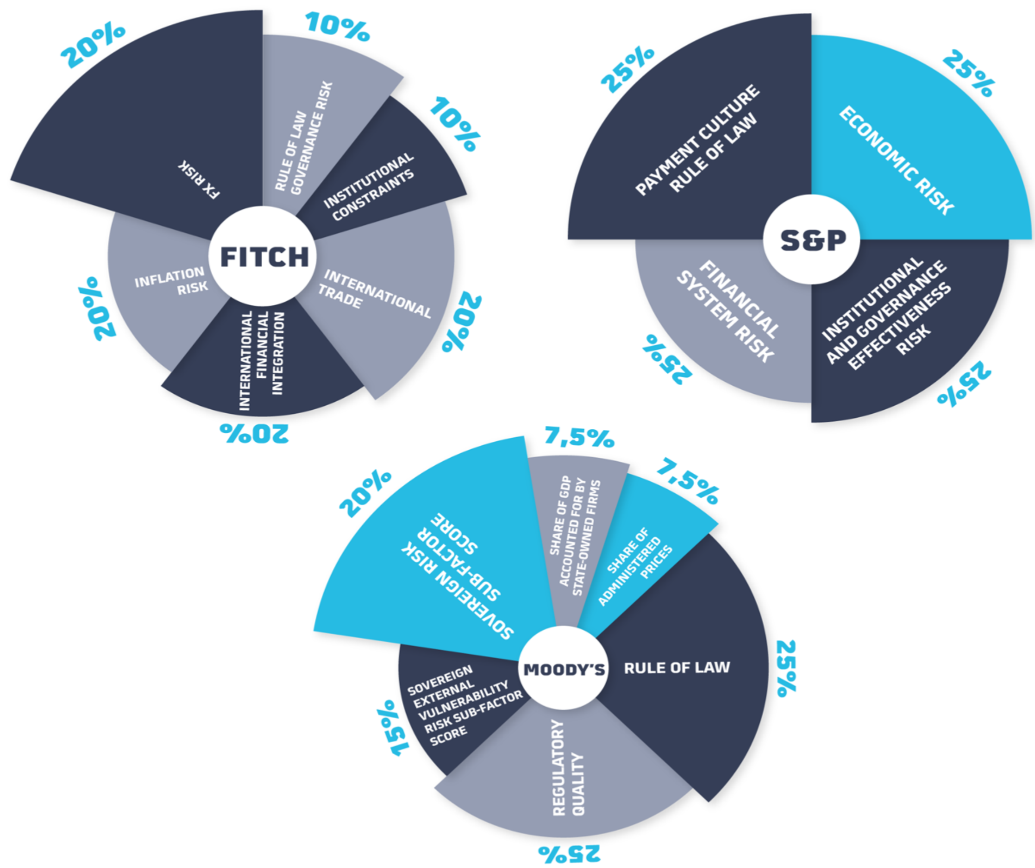
1.4.1 Business Risk Profile

When a credit rating agency performs in-depth analysis, one of the main analysis is to investigate the environment of the company – its business risk profile. The business risk profile comprises of the county risk, industry risk and company-specific risk in which company operates (S&P Global Ratings, 2013). It is critical to analyze the business risk of the company accurately because understanding its risk can be seen as precondition of evaluating its financial risk. If the environment of the company is understood clearly, the analyst can evaluate and define how much debt the company can bear and how aggressive company's financial policy can be, given its business risk profile (Langohr & Langohr , 2008).

Country Risk

The quality of the credit rating can be affected by the country as a result of conducting businesses to, from or within that specific country. Every rated entity's credit risk is influenced in different levels by the risks arising from the country. These risks can be economic, institutional, political, financial, legal and payment culture (S&P Ratings Services, 2013). Sovereign ratings are often used as a proxy of country risk. However, country risk is broader concept than sovereign risk, which is defined as risk of loss in cross-border lending stemming from the events in a particular country. In this definition, cross-border lending refers to all forms included government, banks, corporations or individual in country risk while in sovereign risk it is only restricted to the government of sovereign notion (Claessens & Embrechts, 2002). Correspondingly, sovereign ratings may be misleading for the country-specific risk since it only focuses on the sovereign obligor's ability to pay its debt. Therefore, rated entity also receives the country risk assessment for its country involved (S&P Global Ratings, 2021).

Figure 3: Components of Country Risk Profile and Their Weights for Big Three



Source: Own Elaboration. The data for Fitch is from "[Country Ceilings Criteria: Cross Sector]" by Fitch Ratings, 202. The data for S&P is from "[Country Risk Assessment Methodology and Assumptions]" by Standard & Poor's Financial Services, 2013. The data for Moody's "[Country Ceilings Methodology]" by Moody's Investors Service, 2020.

Every rating agency essentially investigate similar sub-factors when evaluating country risks. However, while calculating the final country risk score, the weights they use for sub-factors differentiates. *Figure 3* shows the components of scoring country risk for Fitch, S&P and Moody's rating agencies and their weights for each component. These sub-factors are subject to qualitative and quantitative considerations. CRAs combine these components and calculate the scorecard, ranging from 0 to 6 for Moody's and S&P while from 0 to 5 for Fitch.

Industry risk

CRAs determine the issuer's rating within the scope of the industry in which issuer operates. Credit rate is affected from industry's competitive intensity and volatility stemming from demographic, social changes as well as from the regulatory and technologic developments (Fitch Ratings, 2020). Therefore, CRAs assess the industry risk factors, such as cyclicality, barrier to entry, material change risk and substitution of technologies and growth trend risk, that affect an entity's credit rating (S&P Global Ratings, 2018). According to Michael E. Porter, attractiveness of the industry is the first main determinant for a company's profitability. Thus, the analyst should be aware of the industry structure because a company can change the existing structure (Porter, 1985). Therefore, the impact of cyclicality on the industry and the barriers to entry due to potential new entrants need to be understood clearly by CRAs in order to analyze the possible future volatility that the company can experience (Langohr & Langohr , 2008).

Company-Specific Risk

The final consideration of the business risk analysis is to evaluate the company to determine how strong or volatile it is compared to its competitors. In order to understand the company's position among its competitors, CRAs identify the main competitive factors of the industry (services, product or service quality etc.) and their underlying drivers (Langohr & Langohr , 2008). CRAs use main components that shapes the company's strengths and weaknesses, which are competitive advantage; scale, scope and diversity; operating efficiency and profitability. Therefore, in order to present a strong competitive position, a company should produce better profitability compare to its peers whereas lower profitability metrics results weaker competitive positions among its peers (S&P Global Ratings, 2021). Moreover, knowing the strength level of a company's market position helps identify the steadiness of the end-market that company serves, demand and diversity of its services/products as well as the company's cost structure efficiency (Berckmann & Berge, Manufacturing Methodology, 2020).

1.4.2 Financial Risk Profile

Another key criterion of in-debt analysis shown in *Figure 1,* is to evaluate the financial risk profile of an entity. The financial risk profile is the outcome as a result of management's decisions about which way the company is funded, how the balance sheet is formed within the scope of its business risk profile and its relevant financial risk tolerances (S&P Global Ratings, 2013). This part is a quantitative aspect of the credit risk rating process focusing on entity's financial overview in order to understand ability of honor its debt obligations (Fitch Ratings, 2020). To do so, financial risk analysis measures are used by CRAs to look the entity' financial strengths and weaknesses (Langohr & Langohr , 2008). Financial ratios are used analyzing the company's leverage and debt measures, cash flow generations and its adequacy, liquidity, profitability and capital structure measures. Every credit rating agency approached in a different way when performing financial ratio analysis, but these are the most common measures used by CRAs.

Leverage and Cash Flow Measures

The trajectory of cash flow's current and projected generation in regard to financial obligation of the company is often used by CRAs as the best indicators to evaluate the financial risk (S&P Global Ratings, 2013). In order to analyze the leverage, initially, CRAs need to determine the company's total financial obligations which are the items on balance sheet that have to paid back, in other words items that create liability (Ganguin & Bilardello , 2005). The companies that have higher amount of debt carry a higher risk of not being able to fulfil their financial obligations, accordingly they tend to have lower credit ratings (Pettit, Fitt, Orlov , & Kalsekar, 2004). On the other hand, cash flow analysis is the most important analysis that leads analyst to the credit risk decision since all the companies' financial obligations such as debt, interest payments, dividend payments, wages, trade receivables and capex, are paid in cash (Ganguin & Bilardello , 2005). However, the evaluation part it not straightforward. Once the financial obligations are identified, still it is not easy to say how much leverage is a danger to the company since it depends on the industry in which the company operates. For example, the industries which have low volatility of earnings able to bear higher leverage for its assigned rating compare to industries of high earning volatility (Fitch Ratings, 2013).

In order to assess the leverage and cash flow measures, CRAs uses similar relevant financial metrics and ratios that complement to each other. For example, S&P uses two core ratios cash flow and leverage ratios which are "FFO to debt" and "debt to EBITDA" while Fitch puts more weight to cash flow analysis of earning, coverage and leverage than just traditional leverage ratios such as "debt to equity" or "debt to capital" (Fitch Ratings, 2020; S&P Global Ratings, 2013).

Another important measure related to cash flow and leverage analysis is the coverage. CRAs use coverage ratios broadly in order to evaluate the company's ability of honor its financial obligations since these ratios provide a perspective of company's health, ability to bear its financial debts and solvency. (Mills & Yamamura, 1998; Nevitt & Fabozzi, 2000). For example, S&P uses coverage ratios mainly as supplementary to cash flow/leverage measures especially for the companies that having weaker cash flow/leverage, coverage ratios become more important in order to understand company's ability to pay its financial debt (S&P Global Ratings, 2013).

All CRAs put great importance on evaluating cash flow and leverage in order to assess credit rating. When the rating CRAs' rating methodologies are investigated, it can be seen that most of their financial and metrics are comprised from cash flow, leverage or coverage measures, these measures are directly integrated into their rating scale definitions.

Profitability

One of the most important factors that affect the credit rating is the profitability of a rated company. Profitability is an important indication for the level of risk that a company carries since the more profitable companies are less likely to go bankrupt (Gonis, 2010). In order to maintain a sustainable cash flow and a competitive position within the industry including spending in marketing, ARGE, factories and other similar necessities, the company needs to generate a profit (Berckmann & Berge, Manufacturing Methodology, 2020). Therefore, the profitability should be evaluated in a holistic manner considering the company's activities as well as its industry and compared with its past earnings and the sector average (Atabey, 2020). For example, S&P calculates profitability ratios based on five-year average and evaluates the profitability ratios within the scope of the industry in which company operates. Moreover, S&P uses the profitability assessment of a rated company as a final decision of its competitive position (S&P Global Ratings, 2013). The three biggest CRAs use Operating EBITDA and EBITDA margin which is EBITDA/revenue, as main profitability indicators but of course there are many other ratios that CRAs use like Return on Capital (ROC), EBIT, EBIT margin.

Liquidity

Since the main purpose of credit risk analysis for an entity is to determine the ability to pay its financial obligation in full or in a timely manner, being able to obtain cash which is liquidity, for the times in need gives company a financial flexibility and as a result avoid any payment default (Ganguin & Bilardello , 2005). Therefore, CRAs need to investigate the potential need of cash and how the company will provide cash in case of need (Langohr & Langohr , 2008). A liquidity measure is generally used more for evaluating short-term ratings by CRAs since the short-term ratings are not only for issuer's ability to repay all its short-term financial debts but also other unsecured obligations in less than one year (Pettit, Fitt, Orlov , & Kalsekar, 2004). Moreover, liquidity analysis is more essential for the speculative grade issuers since the need of liquidity is more expected in low creditworthiness. However, even though a company having stable business position and reasonable level of debt can face liquidity disruptions in case of unexpected adverse event (Ganguin & Bilardello , 2005). Therefore, CRAs need to be aware of liquidity structure of the companies and timing of arising possible liquidity needs.

1.4.3 Supplementary Rating Drivers

Other than the two main credit risk profile analysis, business risk and financial risk, additional rating factors also influence the credit rating decision. Therefore, CRAs also use supplementary rating drivers that support to the final decision of credit rating. Role of management, corporate governance, financial policy and peer comparison are the main factors that will be considered as supplementary rating drivers for credit risk analysis.

Management factor plays a vital role in company's credit rating since the management will keep the company in the balance generating the best possible financial and operating outcome by managing the assets of the company effectively given its business environment (Ganguin & Bilardello , 2005). However, the financial performance of the company is not only affected by the management but also from the corporate governance effectiveness. Corporate governance is subject to asymmetric consideration meaning that when it is adequate or strong, is has little positive influence on credit rating. On the contrary if the CRA observes that weakness in corporate governance damages to investor protection, it can result a negative impact on issuer's rating (Fitch Ratings, 2015). S&P investigates corporate governance under four main areas: ownership structure, financial stakeholder rights and relations, financial transparency and disclosure, and lastly board structure and its process (Standard & Poor's Governance Services, 2004). In this manner, ownership structure is one of the most important elements since it can provide a rating support especially if the parent has high credit rating and the capacity to support the company in times of need. However, at the same time ownership can put financial pressure on the company. For example, high dividend payments can result lower financial stability, or agency costs may arise as a result of a conflict between the owner and the manager (Berckmann & Berge, Manufacturing Methodology, 2020; Brealey, Myers, & Allen, 2014). On the other hand, transparency refers to the timely and adequate disclosure about a company's financial and operating performance as well as its practices of corporate governance (Standard & Poor's Governance Services, 2004). Financial transparency and disclosure are especially crucial in order to reduce the information asymmetry between the company and the investor (Skaife, Collins, & Lafond, 2004). Moreover, according to Skaife (2004), stakeholder relations represent the company's approach to its debt and stakeholder while keeping the balance between the management and these stakeholders. He also found that credit rating of a company is positively associated to weaker shareholder rights as a defense against takeover. Lastly, when evaluating the company's board within corporate governance, analysts investigate its level of independency, knowledge and commitment to fulfill its responsibilities. Furthermore, they also evaluate how effective are the outcomes of board's actions such as management selection, company's risk target, supervision of financial reporting (Fitch Ratings, 2015).

Financial policy clarifies the company's financial profile from a different viewpoint than the conclusions deriving from the standard financial analysis, cash flow/leverage, liquidity, profitability analysis. Therefore, financial policy evaluation is needed in order to understand the level of management's decision effect on financial risk profile because long-term risk due to the company's financial policy may not be fully captured by standard financial analysis (S&P Global Ratings, 2013). S&P and Fitch use financial policy as a supplementary driver for their credit rating processes. On the contrary Moody's uses this as a main rating factor considering the financial policy directly affects the company's credit quality, its debt level and its liquidity management (Berckmann & Berge, Manufacturing Methodology, 2020). Lastly, peer comparison is as important as other supplementary drivers as it gives a reference view for company's ratios within its competitors in the sector. Moreover, profitability ratios are useful measures in order to compare the company with its peers as the earning dynamics can be excellent indicator within the sector. (Ganguin & Bilardello , 2005).

1.4.4 The Final Rating

The final step of the credit rating process is the outcome of the credit risk of a company which is the rating that represents the company's credit quality and its solvency (Langohr & Langohr , 2008). In order to achieve the final rating, first the business risk score and financial risk score identified separately as a result of their analysis which was explained before in the parts of 1.4.1 and 1.4.2. After an assigned score to each risk profile, an appropriate weight is also attributed to each score. As a result, a final credit rating is assigned to the rated company combining its given business and financial risk scores and weights. The scoring part will be explained using the S&P's rating methodology[2].

Business Risk Scoring

Under the business risk profile assessment, as it discussed earlier, country risk, industry risk and market are evaluated. After evaluation of these risk, a score is given combining each component of business risk. *Table 1* shows how S&P identifies a combined evaluation for country and industry risk. As it can be seen in *Table 1,* both industry and country risk have the assessments ranging from 1 (very low risk) to 6 (very high risk). S&P determines an assessment score from the combination of country risk and industry risk as a first step. The next step is to combine the score from country and industry risk (CICRA) with the competitive position

Table 1: S&P's Corporate and Country Risk Assessment for Issuers (CICRA)

	--Country risk assessment--					
Industry risk assessment	**1 (very low risk)**	**2 (low risk)**	**3 (intermediate risk)**	**4 (moderately high risk)**	**5 (high risk)**	**6 (very high risk)**
1 (very low risk)	1	1	1	2	4	5
2 (low risk)	2	2	2	3	4	5
3 (intermediate risk)	3	3	3	3	4	6
4 (moderately high risk)	4	4	4	4	5	6
5 (high risk)	5	5	5	5	5	6
6 (very high risk)	6	6	6	6	6	6

Source: The table is taken from "[Corporate Methodology]", by S&P Global Ratings, 2013

[22] S&P, 2013, Corporate Methodology, November, 1-83, pages 4-8.

assessment which ranges from 1 (excellent) to 6 (vulnerable) in order to active overall business risk profile assessment score, shown in *Table 2*.

Table 2: S&P's Overall Business Risk Assessment

	--CICRA--					
Competitive position assessment	**1**	**2**	**3**	**4**	**5**	**6**
1 (excellent)	1	1	1	2	3	5
2 (strong)	1	2	2	3	4	5
3 (satisfactory)	2	3	3	3	4	6
4 (fair)	3	4	4	4	5	6
5 (weak)	4	5	5	5	5	6
6 (vulnerable)	5	6	6	6	6	6

Source: The table is taken from "[Corporate Methodology]", by S&P Global Ratings, 2013

In order to calculate overall business risk assessment, appropriate weights are assigned to each component of business risk profile. In S&P's example, a weighted average is mostly used with only few exceptions.

For example, few companies can have business risk profile score of 2 with CICRA being 5 if the company's competitive position score is 1 and country risk score is no more than 3. Moreover, in order to make an alteration in the weights, S&P analysts also consider the profitability of the company within its industry average as well as investigate more in detail if the company has a unique competitive position that can create advantage compare to its peers. On the other hand, Moody's defines sub-factors that form business risk profile, rather than evaluating under the main factors (country, industry and company-specific risk), to each sub-industry groups, and assigns the weights as a result of the observations and estimations made by its analysts (Jones & Morrison, 2015).

Financial Risk Scoring

Financial risk profile also needs to be scored as in business risk profile. As a result of the analysis of company's cash flow, leverage, profitability and liquidity measures, the CRA first assigns appropriate weights and scores to these components then calculate overall financial risk score. In S&P's example, the agency focuses cash flow for its financial risk assessment which ranges from 1(minimal) to 6 (highly leveraged). In comparison, Moody's scores each component of financial risk profile separately rather than evaluating these components under a single roof of financial risk score. After these financial risk components are scored, ranging between 0.5 to 20.5, Moody's weights these factors appropriately depending on rated company's sub-industry group (Berckmann & Berge, Manufacturing Methodology, 2020).

Final Risk Rating Determination

After financial and business risk profiles of rated company are scored, the final step is to combine these two to achieve a final rating score. *Table 3* shows S&P's credit risk ratings after the combinations of company's business and financial risk scores. However, *Table 3* presents only the rating above the default or possible default grades[3]. Any rating under "bb-" is subject to different rating criteria in S&P's methodology. To assign "CCC+, CCC, CCC- and CCC" ratings, S&P associates each level of rating to explicit scenario/s (Standard & Poor's Rating Services , 2012).

Table 3: S&P's Combination of Business and Financial Risk Profiles to Determine the Final Rating

	--Financial risk profile--					
Business risk profile	**1 (minimal)**	**2 (modest)**	**3 (intermediate)**	**4 (significant)**	**5 (aggressive)**	**6 (highly leveraged)**
1 (excellent)	aaa/aa+	aa	a+/a	a-	bbb	bbb-/bb+
2 (strong)	aa/aa-	a+/a	a-/bbb+	bbb	bb+	bb
3 (satisfactory)	a/a-	bbb+	bbb/bbb-	bbb-/bb+	bb	b+
4 (fair)	bbb/bbb-	bbb-	bb+	bb	bb-	b
5 (weak)	bb+	bb+	bb	bb-	b+	b/b-
6 (vulnerable)	bb-	bb-	bb-/b+	b+	b	b-

Source: The table is taken from "[Corporate Methodology]", by S&P Global Ratings, 2013

1.5 The Main Historical Events that Shape Today's CRAs

This part will explain the main historical events, represented as an overview in *Figure 4,* that structured today's credit rating agencies. These are collected under three main events. In each event is explained the evaluation of CRAs with cause-effect relationships. Each cause-effect relationship puts building blocks to CRAs' foundation. *Figure 4* shows a timeline that

[3] See *Figure 1*

investigates each time separating into two parts. Left side of the *Figure 4* represent the main events between the years of 1827 and 1975 while right side shows effect of one event to CRAs, written in the box, together with its brief reason, written in the top of each box. Each event and its results in *Figure 4,* already explained in this thesis.

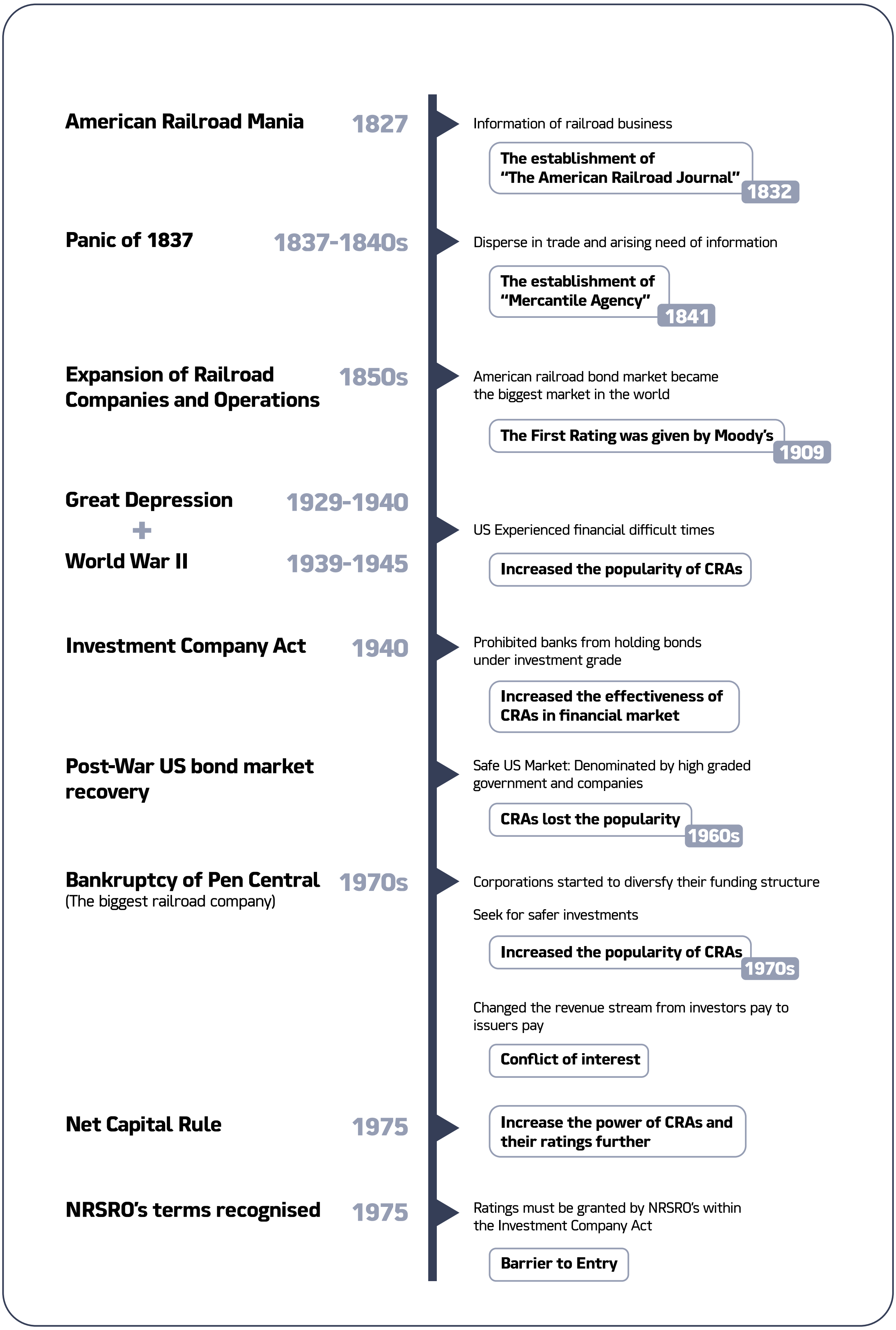
After the World War II (1939-1945), despite the expectation of going back to difficult times similar in Great Depression (1929-1940), the American economy started the postwar period with strong growth. Even, in the 1950s, The United States was described as a time of complacency (U.S. Department of State, n.d.). Credit rating agencies which started their operations successfully in the

1930s. However, their popularities declined by the times of 1960s. The reason for becoming less important; during the time, the U.S. bond market was safer as it was mostly dominated by high graded government and the corporates. Moreover, the markets around the world were barely generating business (Caouette, Altman, Narayanan, & Nimmo, 2008). It can be said that the outlook of the US economic environment at that time made rating agencies less needed.

However, the 1970s started eventfully with the bankruptcy of Penn Central Transportation Company was not only the biggest railroad company, but it was also the 6th largest company in the United States. The company experienced with numbers of failures as it was managing a very complex structure. Moreover, the company issued many commercial papers at rising interest rates in order to keep alive. However, in the end, despite the government's rescue attempt, Penn Central failed in June 1970. It was an important event for the time, causing a shock effect in the commercial paper market (Goldman Sachs, n.d.). Moreover, it was the biggest financial failure in the US's history until the Enron Scandal in 2001 (Duggan, 2018).

Apart from this event, in the 1970s, debt volumes' issuances increased as the corporations began to diversify their funding structures. Consequently, credit rating agencies gained popularity and importance as the investors became more cautious and were ready to pay to find safer investments (Caouette, Altman, Narayanan, & Nimmo, 2008).

Figure 4: Overview of Historical Events Shaping Today's CRAs



Source: Own Elaboration

as a safeguard in the market and big rating agencies expanded their ratings to commercial papers as well (Handal, 1972). Big agencies started to innovate their business models starting with change of their revenue string from investors pay to issuers pay at the beginning of the 1970s and Bankruptcy of Penn Central was a turning point that led to this change (Cantor & Packer, 1995). Nevertheless, according to Lawrence J. White, there are other three underlying motivations of this model change which are listed below (White, 2010):

1. High-speed photocopy machine can allow many investors obtaining photocopies with no charge from their friends
2. Financial regulations stated that issuers are needed to be rated by agencies in order to a financial institution to include its portfolio.
3. The information could be paid for by issuers of debt buyers of debt, or some mix of the two.

Penn Central Bankruptcy

The most critical point of implementing this business model is that it has created a conflict of interest, which is still a current issue since there is still no substitutes for issuer pay model. However, continuation of issuer pay model brings the risk of issuing credit ratings for CRA's large clients' needs to able to boost their business outlook (Bai, 2010). After CRAs change their revenue string model, they also renew their rating representations adding outlook of credit watch, meaning the rating is under reviewed, and symbols of plus and minus in order to provide a better rating classification to investors (Cantor & Packer, 1995).

New Era of Power - Net Capital Rule, 15c3-1

Fifteen years after the first rating given by Moody's, on September 1931, US Comptroller of the Currency (OCC) established a regulation that determines the differentiation the scale of securities as investible (Baa/BBB or higher) and non-investible (lower than Baa/BBB). By doing so, the use of bond ratings started to become official (Fons, 2004). Furthermore, the OCC and the Federal Reserve Board prohibited banks from holding bonds that do not have investment grade by at least two agencies in 1936 and with the Investment Company Act in 1940, they limited money markets funds to "eligible securities" defined by CRAs (Poon, 2012).

In 1975, SEC published net capital rule, Rule 15c3-1, and nationally recognized statistical rating organization (NRSRO) had a role as a part of the agency's determination of capital charges on different grades of debt securities under this rule (Shorter, 2010). This rule imposes to brokers a higher capital reserve requirement on security which are rated below investment-grade bonds. Additionally, the rating must be granted by nationally recognized statistical rating organization (Kruck, 2011). This rule created a barrier to entry for new rating agencies in the US. The bond market information is one where potential barrier to entry like economies of scale, the advantages of experience, and brand name reputation are important features. Nevertheless, in creating the NRSRO designation, the Securities and Exchange Commission had become a significant barrier to entry into the bond rating business in its own right. Without the benefit of the NRSRO designation, any bond rater would likely remain small-scale. (White, 2010)

"We live again in a two-superpower world. There is the U.S. and there is Moody's. The U.S. can destroy a country by leveling it with bombs; Moody's can destroy a country by downgrading its bonds. "By Thomas L. Friedman (Friedman, 1995)

When the phrase NRSRO was first introduced, the three agencies Moody's, Standard & Poor's, and Fitch, were accepted nationally at that time with the implementation of SEC's new capital rule. Nevertheless, over time, as the public bond market and the rating industry grew, other agencies have demanded NRSRO designation from the SEC (Cantor & Packer, 1995). However, it was not easy to be a rating agency accepted by the SEC since it never specified the conditions on how a CRA can become a NRSRO. In the end its approach describes as "we-know-it-when-we-see-it." resulting limited growth in NRSROs' pool was widely believed to have helped to entrench the three dominant CRAs further. Currently, there are only ten rating agencies recognized by NRSRO. Moreover, As the end of 2019, big three rating agencies are rated 95.1% while denominated 93.3% of total NRSRO's revenue (Office Of Credit Rating, 2020).

1.6 The Effects of Credit Rating Agencies

Rating agencies became an essential part of the global financial landscape. For enterprises, obtaining a credit rating is necessary in order to raise funds. CRAs influences on today's financial market significantly affects investors, issuers and governments so the rating actions being closely followed by them (Binici & Hutchison , 2018). Any downgrade action in sovereign ratings results immediately the country's borrowing cost to increase (European

Commission, 2013). On the other hand, the effect of CRAs to investors is also an influential tool in order to minimize the risk of their investing (Solovjova, 2016).

There are many researchers investigating the effect of CRAs opinion and their ratings on countries, their creditworthiness, their macroeconomics and indirectly microeconomics balances. A research conducted by Ntsalaze (2016) shows that sovereign ratings constrain to corporate ratings as well showing the example from South Africa which have a speculative sovereign grade, not only affecting the government itself but also limiting the companies' ability to find a secure investor funding from international financial market at competitive rates. Host et al. (2012) emphasizes that CRAs is a significant factor to financial market. Moreover, Gossel and Mutize, (2018) found that sovereign ratings are responsible to adverse macroeconomic conditions not only to rated country but also the financial markets of the neighboring countries as a result of sovereign ratings' spillover effects. Working paper by Ryan, (2012) points out the excess power on countries' financial market caused and worsened Eurozone crises following the banking crisis in 2008 due to the failure of their assessment. However, despite the many research about the impact of CRAs on countries and the financial market players within the country (investors, lenders, issues and companies), there are also another affected party that is not as investigated as but should not be neglected: individuals and households. Wu, (2018) approached the results of CRAs' actions from a broader perspective. She explained the domino and loop effect of downgrading a federal government's rating referring also to how this effect can be passed on to the households. She explained this situation starting from the consequence of downgrading the government's rating, which will imply also downgrades for corporations. This will lead corporates to borrow at higher cost so their response will be the cutting the new investments which slows down the economy. This economic slowdown will put further pressure on government's rating, loop effect, moreover once the banks face higher borrowing cost, they will transfer this to the households as higher rates of lending or will be cut from their deposit account rates (Wu, 2018).

Against all the possible effects, credit ratings remain a global benchmark for the creditworthiness of assessment in capital markets, but when this benchmark is used as a purpose of regulatory or in critical private covenants, any defect in their role can have trigger effect related to the credit ratings (Papaikonomou, 2010).

Chapter 1 reviewed the theoretical information of CRAs informing its history, traditional rating methodology and its effects to countries, financial players as well as to individuals. However, it should be noted that, explained methodologies are found in credit rating agencies' websites, there are parts that remain blurry regarding the weights because this is the information they provide. All of the credit rating agencies provide general similar information about their rating methodologies without being precise. There are debates on how much precise they need to be. Of course, it normal to expect that the rated entity and the investors want to know about rating methodologies and processes in more detail on the other hand, CRAs do not want to reveal some parts on how they are rating the entities as that may hinder the processes because if the companies know how they are or are going to rated, there is a risk that rated entity may mispresent the information or adapt to this rating processes. In Chapter 2, the theoretical background of FinTech will be introduced together with its use in credit risk assessment by investigating the first FinTech credit rating agency; ModeFinance.

CHAPTER 2: FINANCIAL TECHNOLOGIES (FINTECH)

Chapter 2 reviews the theoretical background of FinTech. This chapter starts with the description and history of FinTech, explain its dimension and concepts. After, this chapter continues with the introduction of the technologies used in credit risk rating assessment. Moreover, this chapter will describe the Fintech Credit Rating Agency and its rating methodology by investigating a company of Modefinance. Finally, Chapter 2 will be concluded with a brief view on the effects of Fintech.

2.1 The Rise of Fintech and its Definition

Fintech is a financial innovation enabling from technology. This technology can result in new products, business models or applications that will have a material impact on financial markets, institutions and the providing of financial services (Bazarbash, 2019). Today, fintech simply is seen as a combination of information technology and financial services.

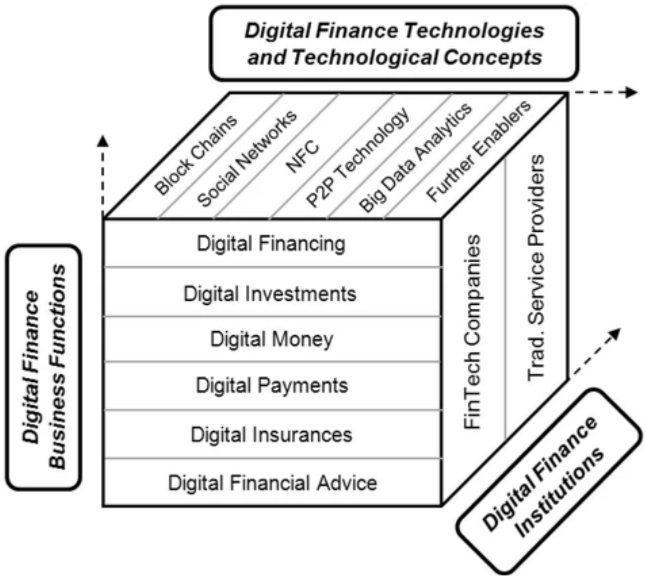
Financial technology has a long history, but Fintech is a relatively new terminology born as a project under the name of Financial Services Technology Consortium by Citigroup in the early 1990s. Citigroup initiated this project with the slogan of “Times have changed” to change its reputation of resisting technological developments (Hochstein, 2015). Despite its long past, FinTech has become popular since 2014 (Interest over time: Fintech, n.d.). Fintech realized a robust continues growth since then and became an indispensable and fundamental part of finance. Even though FinTech recently has become a known word, in reality, it has a long history. Douglas W. Arner, Jànos Barberis and Ross P. Buckley (2016) show the history of Fintech dividing by three eras starting from 1866 (Arner, Barberis, & Buckley, 2016). Goetzmann and Rouwenhorst (2005) documented 19 major financial innovations that vary from the innovation of interest to Eurobonds' invention having 4000 years of history (Lerner & Tufano, 2011).

The next chapter will look at Fintech in more detail explaining its concepts and dimensions.

2.2 Fintech and its dimensions

Together with the development of technologies, the institutions driving by the financial industry have to upgrade their business model by branching out from using only standard financial methods. Companies in almost every sector, especially in the finance sector, are forced to learn how to integrate these technologies into their business structure in order to be developed or even survived. Moreover, the encouragement of technological development and its integration became even more vital in today's world. Because beneficial effects from these technological innovations within the sector will increase productivity together with better investment decisions and more savings. Therefore, the application of these innovations will have an impact not just in company-wide but also economically as a result of better finance (Frame & White, 2004).

Figure 5: The Digital Finance Cube and its Dimensions



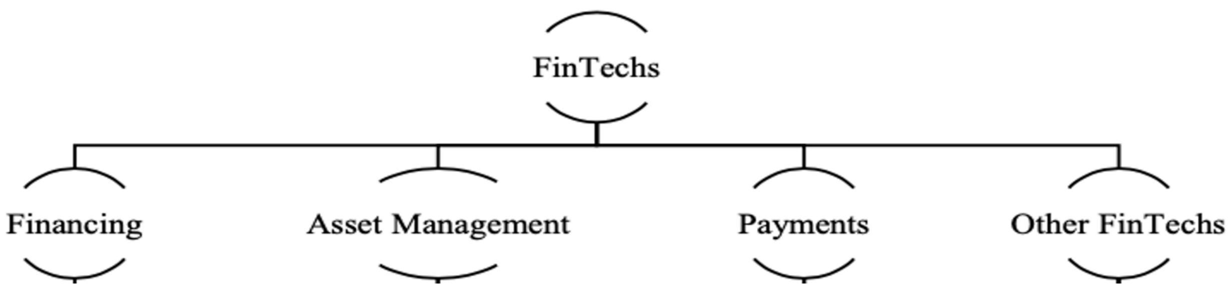
Source: The figure is taken from [Digital Finance and FinTech: Current Research and Future Research Directions] by Gomber et al., 2017

Fintech is a broad concept. Every sector applies and develops different technologies in accordance with their needs. There is significant academic research on Fintech yet there are still many unexplored new horizons of Fintech that can only be revealed by new fintech companies (Zavolokina, Dolata, & Schwabe, 2016). Gomber et al. (2016) developed a framework representing the existing literature as well as enabling to identify undiscovered territory in fintech linking with digital finance. *Figure 5* represents this framework called Digital Finance Cube showing three dimensions of Fintech which are digital Finance business functions, relevant technologies and technological concepts, and institutions providing digital finance solutions (Gomber, Peter; Koch, Jascha-Alexander; Siering, Michael;, 2017). The first dimension of the cube is the business functions covering the most known financial services from a business administration point of view as financing, investment, money, payment, insurance and lastly financial advice. The second dimension comprises from the digital finance technologies and technology concepts that cover the technologies and their concepts enabling functions from the first dimensions. These are the technologies like block chain, social networks, P2P system, big data analytics and further enablers (internet, artificial intelligence, mobile devices etc.). Lastly the third dimension is digital finance institutions representing both FinTech companies and the traditional financial institutions. Two of them are a function of Fintech because not just Fintech companies drives the change in digital finance, but also traditional financial institutions provide new Fintech services adopting new technologies (Gomber, Peter; Koch, Jascha-Alexander; Siering, Michael;, 2017).

2.3 Fintech Applications

Fintech is a wide concept having many applications in financial market. Dorfleitner & Hornuf (2016) divides the fintech industry into four major segments: Financing, asset management, payment transaction and other fintechs. *Figure 6* illustrates these four segments and their subcategories.

Figure 6: FinTech Company Segments

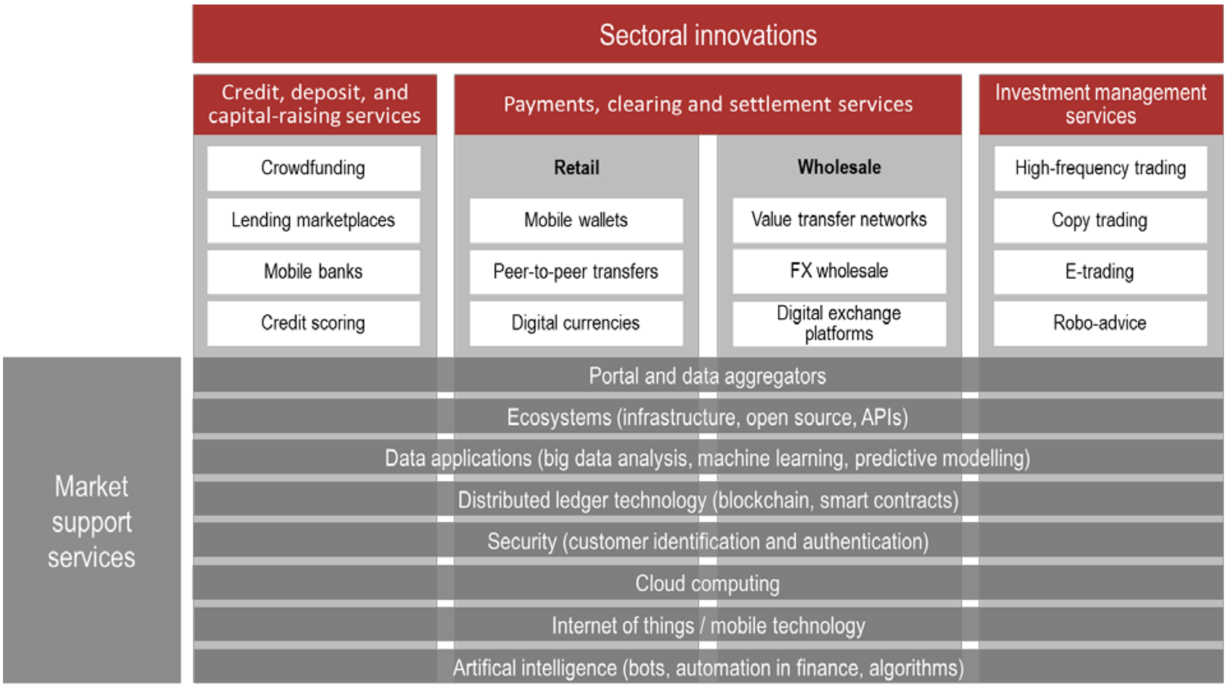


Source: This figure is taken from [The FinTech Market in Germany] by Dorfleitner, 2016

Report from IOSCO Research Report on Financial Technologies (Fintech), 2017, illustrates the Fintech's applications under the main eight categories: Payment, insurance, planning, lending/crowdfunding, blockchain, trading & investments, data & analytics and security. On the other hand, as shown in *Figure 7,* the Basel Committee on Banking Supervision classifies Fintech industry to three product sectors that are directly related to the core banking system and additionally market support services segment that contains innovations and new technologies. BCBS puts market supports services into different categories because the technologies and innovations used in this segment is not directly related to the financial sector but plays an important role in developments of fintech (Basel Committee on Banking Supervision, 2018).

As it can be understood that Fintech exists in many sectors and its technologies differentiates as with the sector. As fintech has wide applications, this thesis will be focused on only fintech technologies and its products related to the credit rating agencies. Therefore, in the next part, the technologies that are used in credit rating evaluation will be explained.

Figure 7: Sectors in FinTech



Source: This figure is taken from BCBS, https://www.bis.org/bcbs/publ/d431.pdf, 2018

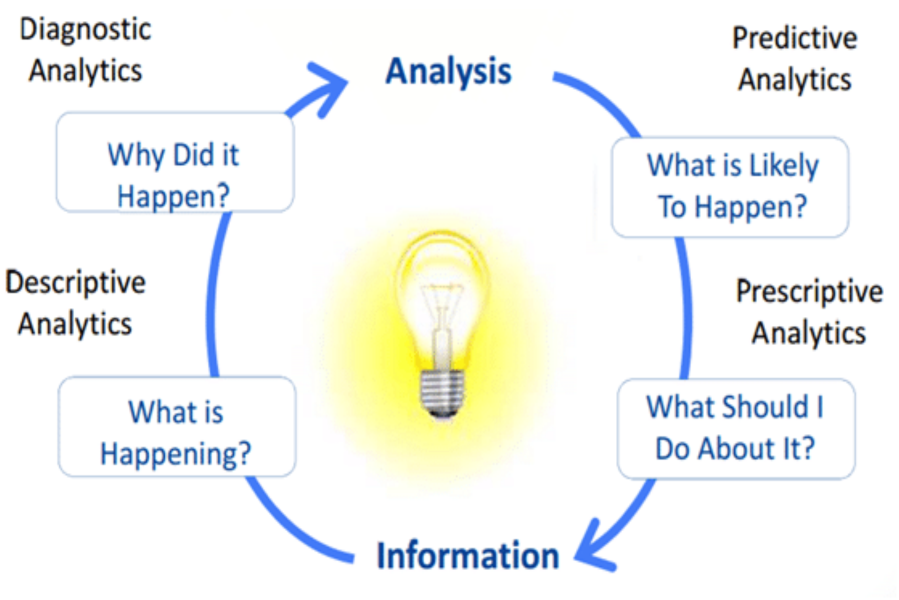
2.4 The Main Technologies in Credit Rating Evaluation

In this part, the major technologies used in credit risk rating assessment will be explained. There are three major technologies used by finance sector: big data analytics, artificial intelligence and computational finance.

2.4.1 Big Data Analytics

Big data analytics is an advanced analytic technology to extract meaningful insights from very large, diverse big structured, unstructured, or semi-structured data sets to hidden patterns, unknown correlations, market trends (Sathi, 2012; Simplilearn, 2021). As with the fast and constant grow of finance industry bring the millions of data along. Analytic process of these big data creates a powerful tool of data analytics for providing a strategic advantage and identifying new emerging business opportunities (Ajah & Nweke, 2019). Therefore big data analytics plays a significant role in financial services sector, especially in trading and investmenting, fraud detection and investigation and risk analysis (Hasan, Popp, & Oláh , 2020) Ajah et al. (2019) cathegorised the approaches of big data analytics as descriptive, predictive,

Figure 8: Approaches of Big Data Analytics



Source: This figure is taken from [A Roadmap Towards Big Data Opportunities, Emerging Issues and Hadoop as a Solution] by Risa Quayyum, 2020

diognostic and prescriptive. *Figure 8* provides short decriptions on these approaches. Big data is an important tool in credit risk assessment as this this technology enables the analyze high volume of data in short time. Furthermore, big data is an important tool not only helping financial institutions to describe what already happened in the past but also predict what might happen in the future (He X. J., 2014).

2.4.2 Artificial Intelligence

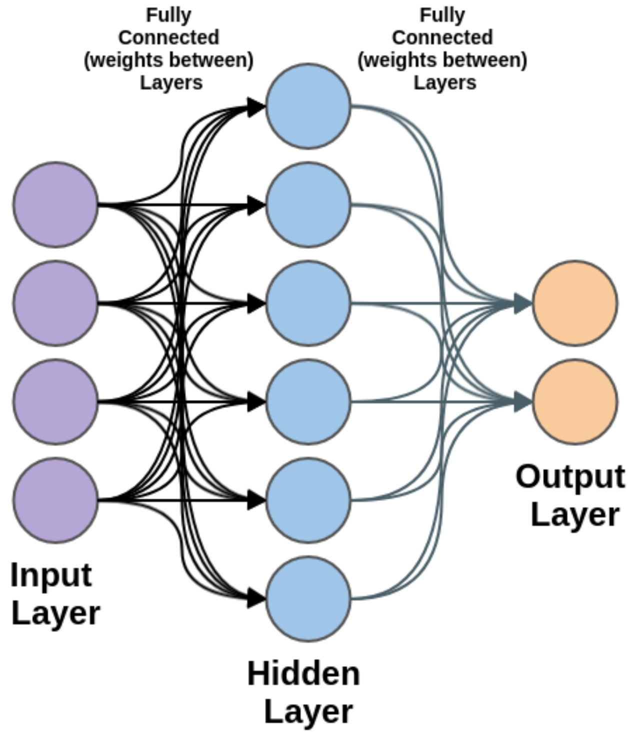
Artificial Intelligence (AI) was initiated with a proposal of John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon at the Dartmouth College in 1956 (McCarthy, Minsky, Rochester, & Shannon, 2006). Financial institutions who integrate fintech promoted by artificial intelligence and machine learning (ML), into their operations resulted in more efficient results; consequently, AI became extremely popular in finance with its rapid development (Xie, 2019). AI refers to the general rules of computers to mimic human mind while ML is the subset of AI, in which machines are capable of performing actions based on past experiences and decide (IBM Cloud Education, 2020).

Even though AI is an extensive field that combines multiple approaches, most of the interest in this field is concentrated on ML which is the most popular AI approach to date. ML deals using data progressively to adapt the parameters of statistical, probabilistic, and other computing models and, automates one or several stages of information processing. There are numbers of techniques of ML but the most known techniques in finance are artificial neural networks (ANNs), fuzzy logic, genetic algorithms, decision trees and random forests (Bartram, Branke, & Motahari, 2020) In the next part, these tools will be summarized.

Artificial Neural Networks

Artificial neural networks (ANN) are very powerful techniques of AI. ANN is a computational model that mimics human brain in a way of processing information. ANN comprises from large number of connected processing units inspired by animal's central nervous systems (Sharmma, 2017). ANN captures the structured knowledge and analyses trained neural network (Kasabov, 1996). There are many applications of ANN, but most frequently use of ANN in credit scoring model is called Multi-Layer Perceptron (MLP) which is developed by Security Pacific Bank (West, 2000). MLP comprises from three types of layers each having different roles called input, hidden and output layers as in ANN. Each layer contains given number of nodes together with their activation function and neighbor layers are linked by the given weights which is represented in *Figure 9* (Munkhdalai, Namsrai, & Munkhdalai, 2019).

Figure 9: ANN: Multi-Layer Perceptron (MLP)



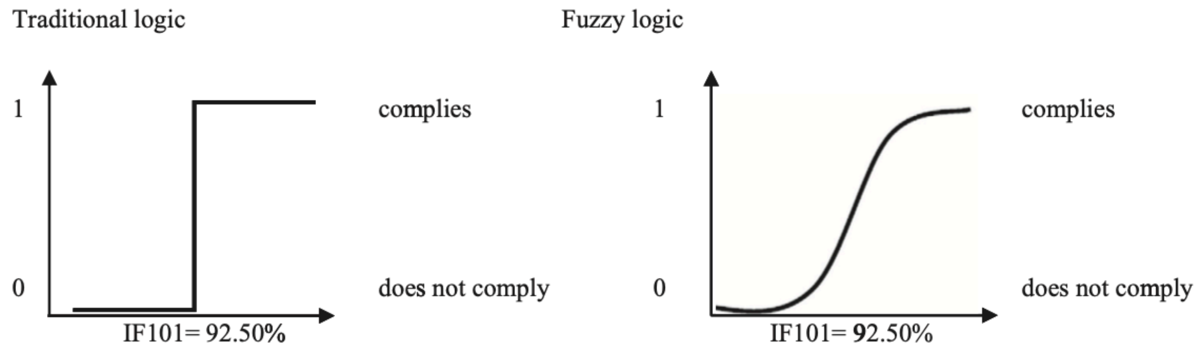
Source: This figure is taken from the website: https://austingwalters.com/classify-sentences-via-a-multilayer-perceptron-mlp/, 2019 by Austin G. Walters

Fuzzy Logic

The concept of Fuzzy set was introduced by Lotfi Zadeh in 1965. Based on this concept, he later developed many of the methods of fuzzy logic (Kasabov, 1996). Fuzzy logic is be seen as an extensive version of classical logical system. Fuzzy logic provides a conceptual framework when dealing with the problem of knowledge coming from the environment of uncertainty (Zadeh, 1992). In another word, the goal of fuzzy logic is to mimic the uncertainty and imprecision of human thinking using the appropriate mathematical tools (Sanchez-Roger, Oliver-Alfonso, & Sanchís-Pedregosa , 2019). Díaz Córdova el at (2017) presents the interpretation of traditional and fuzzy logic as in Figure 10, emphasizing the strong change in the curve between the proposed ranges. Figure 1 shows the how the fuzzy logic captures the vagueness compare to precise result in traditional logic.

When fuzzy logic is used in problem solving, one of the most important tools of using fuzzy logic is representing the problem in fuzzy terms which called conceptualization. In this process of problem's identification, linguistic terms are mostly used such as high, low, very strong etc. This linguistic term called "score" it the values are represented with high and low, as in credit risk scorings (Kasabov, 1996).

Figure 10: Interpretation difference between traditional and fuzzy logic



Source: This figure is taken from [Fuzzy logic and financial risk. A proposed classification of financial risk to the cooperative sector] by Diaz Cordova el at., 2017

Sector Vector Machine (SVM)

SVM is the type of machine learning that also used in credit rating assessment. It is first introduced by Vapnik in mid of 1990. SVM provides a model with independent learning ability to solve the high dimensional problem. SVM has many financial applications, especially in time series prediction and classification, and is used in credit rating assessment with comparative studies (Li, Liu, Xu, & Shi, 2004).

Genetic Algorithms

Machine learning works with set of the designs of algorithms that allows computers to advance behaviors based on empirical data so; machine learns the computer learns as well. (Bhasin & Bhatia, 2011). In that matter, genetic algorithms (GA) can be used for learning functions without need of making assumption on the nature of the function (Fogarty, 2012). GA is the stochastic search technique enabling to search large and complicated spaces on the ideas from natural genetics and evolutionary principle (Gordini, 2014). Genetic algorithms are mostly used in two ways for credit scoring: the first is in hybrid approach meaning GA is used with other methods like neural networks while second is in standalone (VaclavKozeny, 2015).

GAs are being used with other methods such as neural network. Both ways can be used in credit scoring models. Gordini (2014) used the genetic algorithm in order to predict bankruptcy in SMEs with using GA standalone.

Decision trees and Random forests

Decision trees are versatile algorithms in order perform classification and regression task by generating tree like structures (Madaan, Kumar, Keshri, Jain, & Nagrath, 2020). A decision tree sequentially splits a dataset into increasingly small subsets typically based on a single feature value (Breiman, 2004). On the other hand, random forests are uses set of decision trees that evolve in subspaces of data which are selected randomly to build predictor sets (Addo, Guegan, & Hassani, 2018). Random Forests are an accurate algorithm that has a great ability to handle thousands of variables without causing deterioration in accuracy. The final outcome in random forest is produced by using majority voting method among the trees because when are thousands of features, weak relevant features may not be appeared in a single decision tree. Many semi-supervised algorithms are used the tools based on the random forest approach (Tanha, Someren, & Afsarmanesh, 2017). The important function of random forest is the algorithm used in predicting missing data in dataset. Therefore, random forest is commonly used in credit risk applications managing row data processing well without adjustments and imputation of missing values (Grennepois, Alvirescu, Bombail, Dessens, & Mikdad, 2018).

2.4.3 Game Theory

Game theory is described as a study that produce outcomes according to the preferences and interacting choices of economic agents where the outcomes can be unexpected by those agents (Ross, 2019). Game theory provides a methodology that bring insights on unexplained phenomena by allowing strategic interaction and asymmetric information that can be included into the analysis (Allen & Morris, 2001) Game theory has a wide of application in finance. However, application of game theory in credit rating assessment is limited. Therefore, its application will be explained from the methodology used in Modefinance which is a Credit Rating Agency. In rating analysis of Modefinance, there number of financial ratios that need to be taken under consideration and identified the “good” ratios. Lowest financial risk is identified by company having the best ratios. In this matter finding these ratios is not easy because, these ratios are subjected to multi-objective optimization problem. Therefore, in order to solve this problem, the game theory, more specifically, Pareto theory is used. The company having “high” rating class is the company that meets the optimum point as a result of pareto (modefinance, 2018). In this manner, multi-objective optimization (MOO) defined as the process of optimizing of two or more conflicting objectives subject to certain constraints in a simultaneous way (Chakrabortya, Das, Barman, & Mandal, 2016). When a MOO problem arises, as in financial ratios, the set of optimal compromise solutions are necessary, Pareto Theory allows the decision maker or the designer to carry out the best choice identifying an effective and complete search procedure (Chiandussi, Codegone, Ferrero, & Varesio, 2012). Pareto optimality is a measure of efficiency while its outcome of a game is called Pareto optimal which is defined as a solution to the MOO problem (Park, Shin, & Tsourdos, 2019).

In this part main technologies that used in credit rating assessment, credit scoring was explained. These technologies are identified mostly referencing from the only ESMA registered Fintech Credit Rating Agency: ModeFinance. The part 2.5 will look Modefinance Company, its ratings and methodologies more closely.

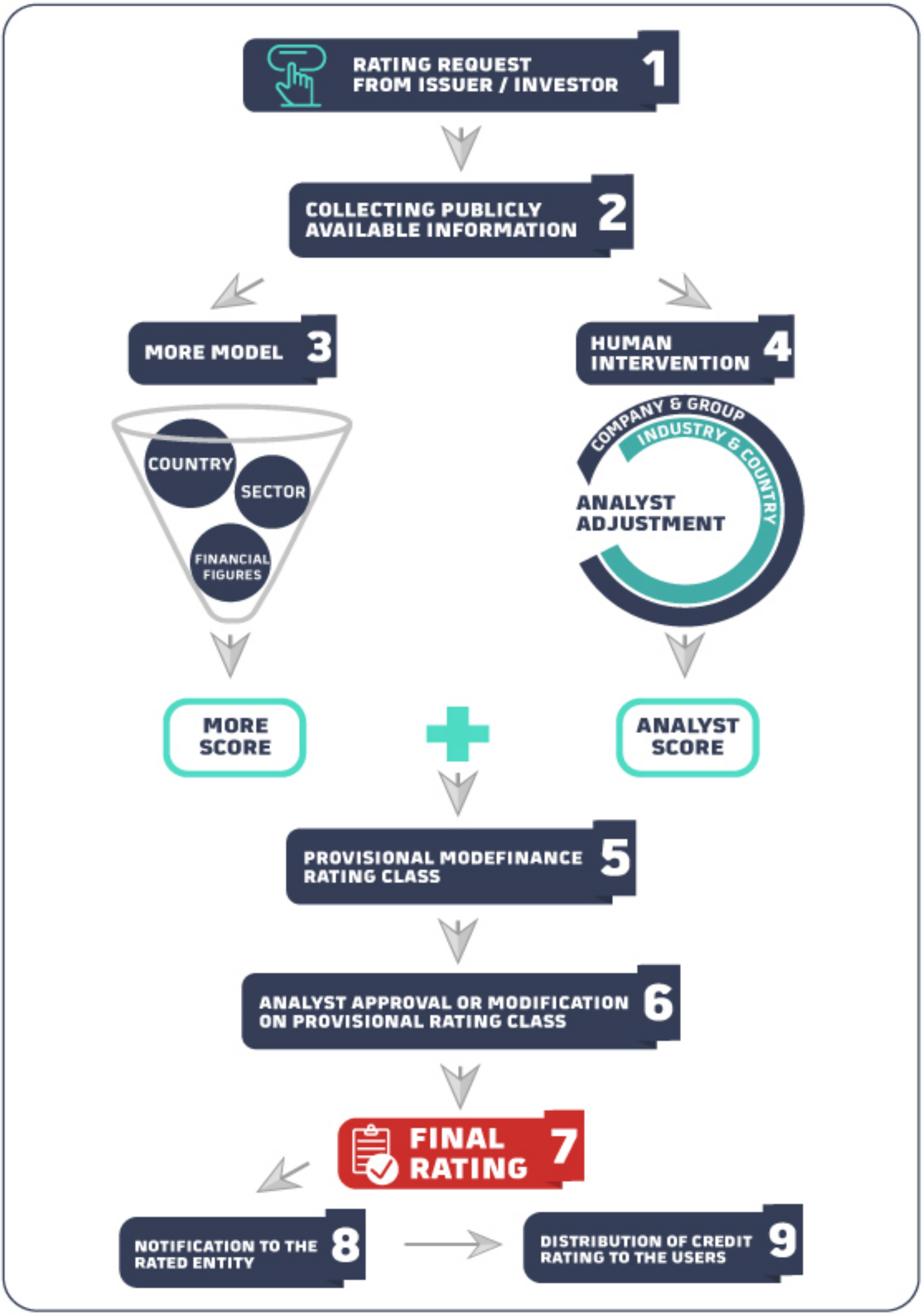
2.5 Fintech Credit Rating Agencies: modeFinance

In this part Fintech CRA, Modefinance, will be explained in more detail. Since this company is the only Fintech Credit Rating Agency registered by ESMA, its methodologies will be discussed as a real case example.

2.5.1 Company Introduction and Its Ratings

Modefinance is an Italian company, was founded by Valentino Pediroda and Mattia Ciprian in 2006, starting its operations to solve financial problems with an engineering approach. The company signed an agreement in 2006 with Bureau van Dijk which is Moody’s analytical company providing data of business information. After the agreement was signed in the same year, the company first distributed its ratings, MORE Ratings, through AMADEUS database after that BvDEP, ORIANA and ORBIS. On July 2015, modeFinance was registered as a Credit Rating Agency under the Article 16 of the CRA regulation by European Securities Market Authority ('ESMA') and started its operation by evaluating corporates creditworthiness. In 2016, the company extended the registration as a Credit Rating Agency and also included bank evaluation into its structure. (modefinance, n.d.) The company is using both subscriber-pays model which the ratings are paid by the subscribers and issuer-pay model which the rating is paid by the rated entities. ModeFinance is an important company because it is the first ESMA

Figure 11: ModeFinance Credit Risk Rating Process



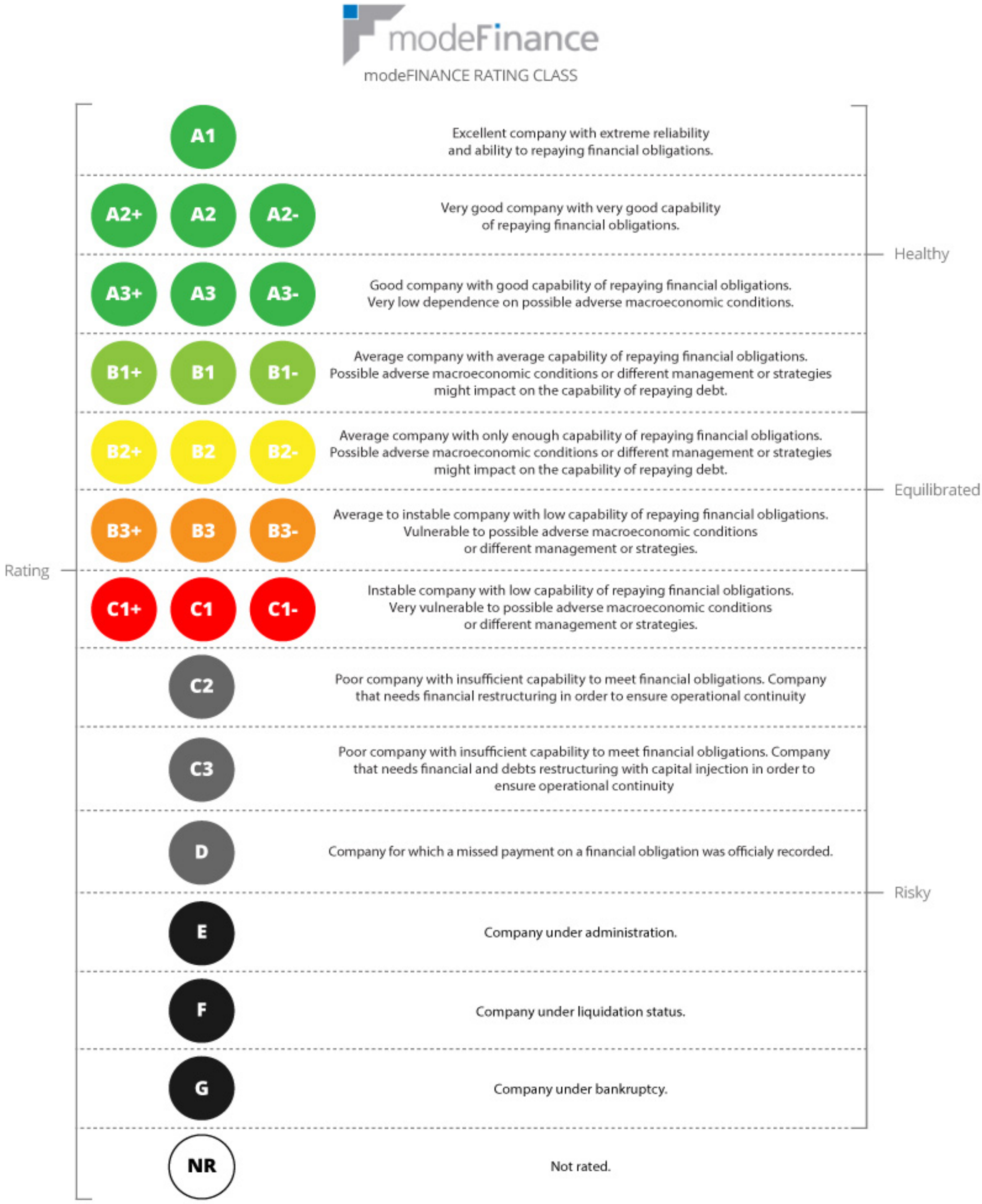
Source: Own Elaboration, the information in this figure is collected from ModeFinance's website

Artificial Intelligence technologies, such as Neural Network Machine Learning models, Fuzzy Logic and Genetic Algorithms. As a result, it produces an integrated web and cloud-based systems (modeFinance, n.d.).

Figure 11 provides the general view for credit rating process of modeFinance. After a rating request from an issuer or investor, the rating process starts with searching for publicly available information for the entity to be rated. There are two main steps in modeFinance credit rating's methodology. First is the evaluation from modeFinance's MORE Model (Multi Objective Rating Evaluation) and second is the evaluation from company's analyst. Initially, by using the collected data on step two in *Figure 11,* a MORE Score is produced from the MORE Model. Meanwhile an

assessment is carried out by the analyst for the company and its group, and its industry and country. Outcome from analyst assessment which is a scale between -0,1 and 0.1, added to MORE Score. The sum of these two scores, a score from the MORE model and score by analyst' assessment, constructs the provisional modeFinance Rating Class. The analyst can either change this provisional rating class by intervening upwards or downwards to maximum one of the rating class or leave the provisional score without making any change. The final adjustments done by the analyst creates a final credit risk rating. After the approval of final credit rating, the rated entity is informed and the credit rating is distributed to the users, modeFinance's subscribers. *Figure 12* shows final the rating scales for modeFinance. The ratings comprise from 21 different classes. The ratings start with the highest "A1" while ends with the lowest "C3". The entities rated A1 represents the meaning of highest creditworthiness while C3 are the lowest. Apart from these ratings, modeFinance also uses scales to the companies which are defaulted and under the bankruptcy process. In the next part company's rating methodology will be explained in more detail. Every information for its methodology was taken from company's website.

Figure 12: ModeFinance Rating Scale



Source: This figure is taken from https://cra.modefinance.com/en/methodologies/companies

2.5.2 The Rating Methodology of modeFinance

"Companies don't die of heart attacks," he says. Their deaths "aren't unpredictable. They usually follow a long disease." Mattia Ciprian

Corporate ratings issued by any rating institutions is a result of the combination of quantitative and qualitative approaches. The process of modeFinance follows the same path as other traditional rating agencies. The company is using two methodologies: the first is *MORE* which is an entirely automated quantitative method that company developed; the second is *RATING* which is a qualitative method that requires rating analysts' involvement for the activity of issuance, monitoring and publication of credit ratings. (modeFinance, n.d.)

The company currently is rating the corporations and the banks. By default, this thesis will describe the corporate rating methodology of modeFinance with three main parts: MORE Model, human intervention and final rating.

MORE Model

The Multi Objective Rating Evaluation (MORE) model was developed by modeFinance to assess industrial companies' level of distress. As shown in *Figure* 11, the first step is searching for the publicly available information for the corporation to be rated. This information includes the company's financial figures, country and sector information which the company shares the same and related product or service. After gathering all the information available, the second step is to assign a risk class. The MORE Model uses these collected and provides opinion on company's creditworthiness by producing a risk class (MORE class). As it can be seen in *Table 4,* these classes start with "AAA" representing a healthiest company and ends with "D" representing the riskiest one. The score produced by MORE model is used as a fundamental base for credit rating assessment (modeFinance, 2017).

Table 4: MORE Scores

Macro category	MORE Class	Assessment
Healthy Companies	AAA AA A	The company's capacity to meet its financial commitments is extremely strong. The company has a strong creditworthiness. The company has a high solvency.
Balanced Companies	BBB BB	Capital structure and economic-financial equilibrium are considered adequate. The company's performances are adequate considering the sector and the country in which it's operating.
Vulnerable Companies	B CCC	The company presents vulnerable signals with regard to its fundamentals. The company has a dangerous disequilibrium on the capital structure and on its economic and financial fundamentals.
Risky Companies	CC C D	The company shows signals of high vulnerability. The company shows considerable pathological situations. The company has no longer the capacity to meet its financial commitments.

Source: This table is taken from [The Multi Objective Rating Evaluation (MORE), by modeFinance, 2017

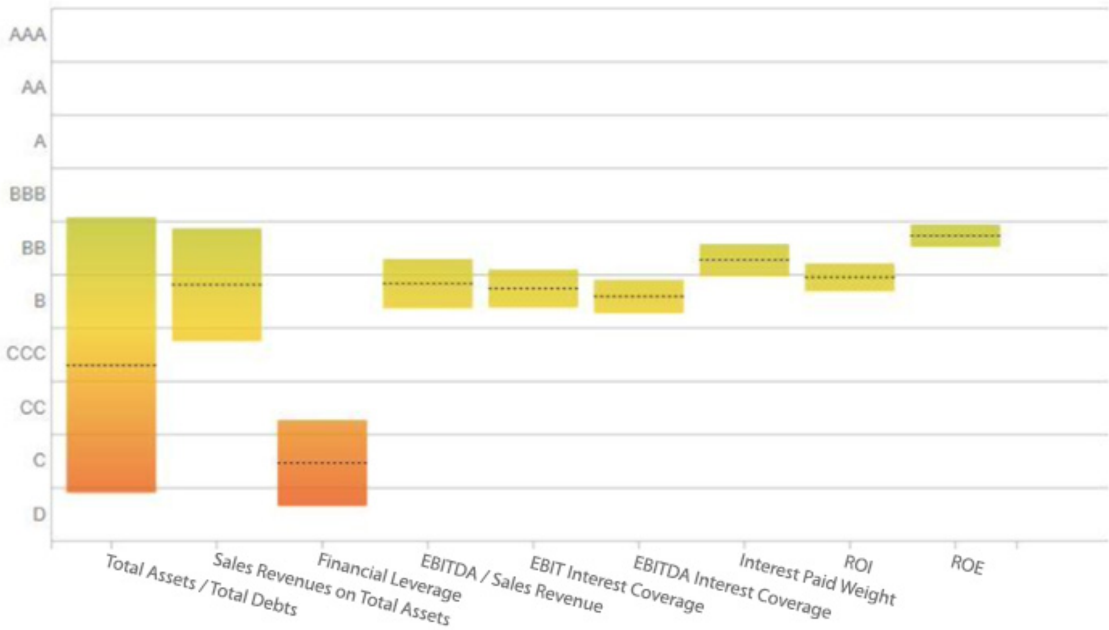
The MORE Model is what makes modeFinance, a fintech credit rating agency, different from other traditional credit rating agencies. MORE model used a multidimensional and multi-objective algorithm that generated by 40,000 different models (~150 countries x 9 sectors x 2 accounting standards x ~15 ratios). The model produces classification for each company using the factors that determine the firm. In order to evaluate the creditworthiness of the company, firstly MORE selects an appropriate model according to the properties of the company which are the industry, region/country and accounting receivables. The selected model uses 15 ratios which comprise from five different category: solvency, liquidity, profitability, interest coverage and efficiency. The ratios are determined in according to two criteria as follows:

1. The ratios must be predictive of default. It is only possible when the necessary information is available about defaulted companies.

2. The ratios must reflect the financial and economic behaviors of a company. Main idea of the model is to create a score class that pictures financial and economic equilibrium belonging to the company.

MORE model first analysis the ratios according to their sensitivity and their strategic relevance. *Chart 1* provides the evaluated company's sensitivity to financial shocks by measuring how ±20% change in a ratio would have an influence on its relative score. In order to measure this sensitivity modeFinance uses its artificial intelligence methodology. This chart is created by comparing company's financial ratio from its financial statement with average values from its sector average values. Dash line in *Chart 1* represents the company's score of each ratio while the bars show the shifting that may cause score change. For example, according to the *Chart 1*, total assets/total debts ratio presents more sensitivity to financial shocks compared to ROE.

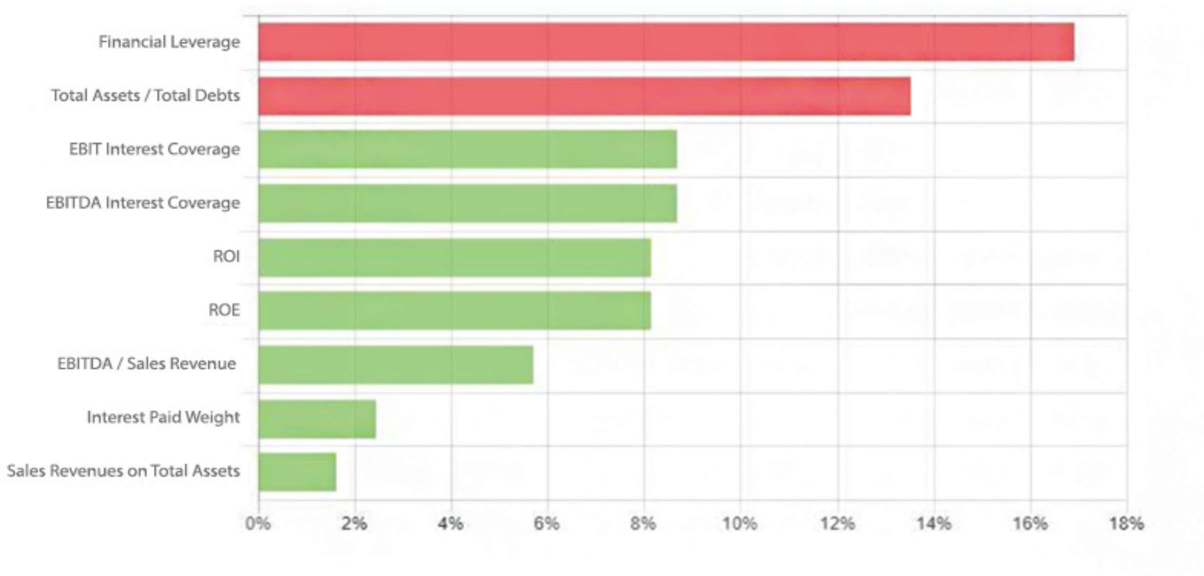
Chart 1: Sensitivity of Ratios



Source: This chart is taken from [Sensitivity analysis: how to evaluate the company's financial resilience], by modeFinance, 2018

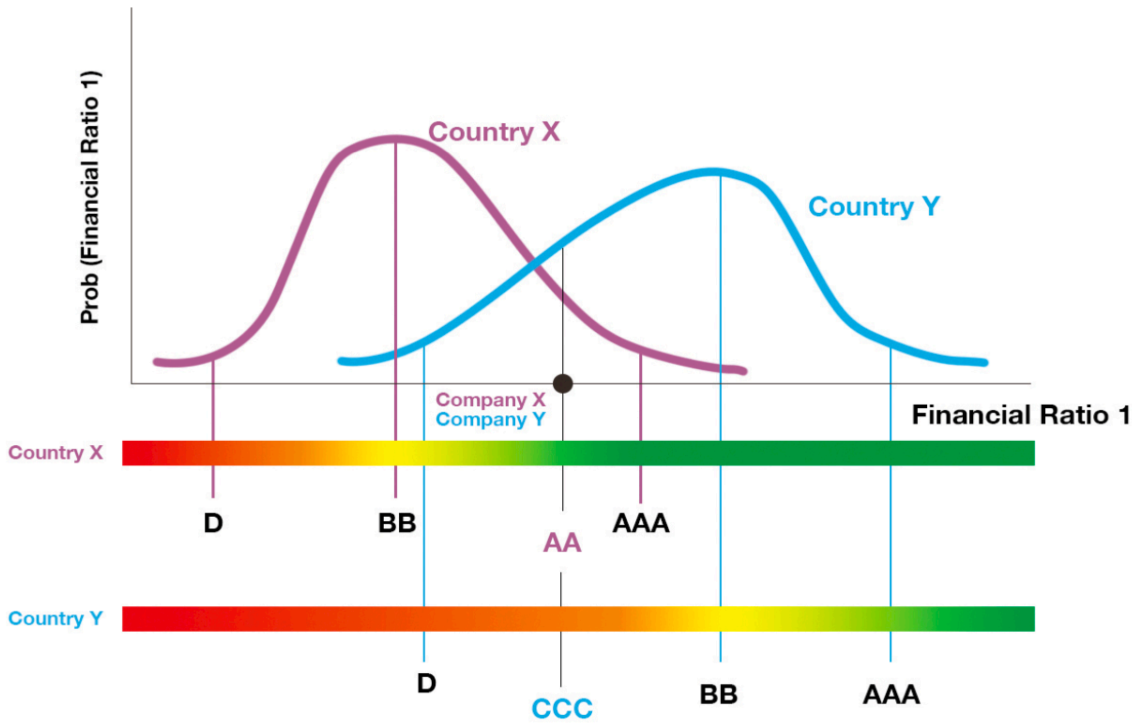
On the other hand, *Chart 2* provides the ratios' contribution weights according to their strategic relevance. These weights are assigned using the strategic interaction principles of game theory. If the bars are red, these ratio scores are lower than company's total score; if it is green, it is vice versa. For example, according to the *Chart 2,* financial leverage ratio has the highest contribution compare to total score and its ratio is lower than the company's total score.

Chart 2: Contribution Weights of Ratios



Source: This chart is taken from [Sensitivity analysis: how to evaluate the company's financial resilience], by modeFinance, 2018

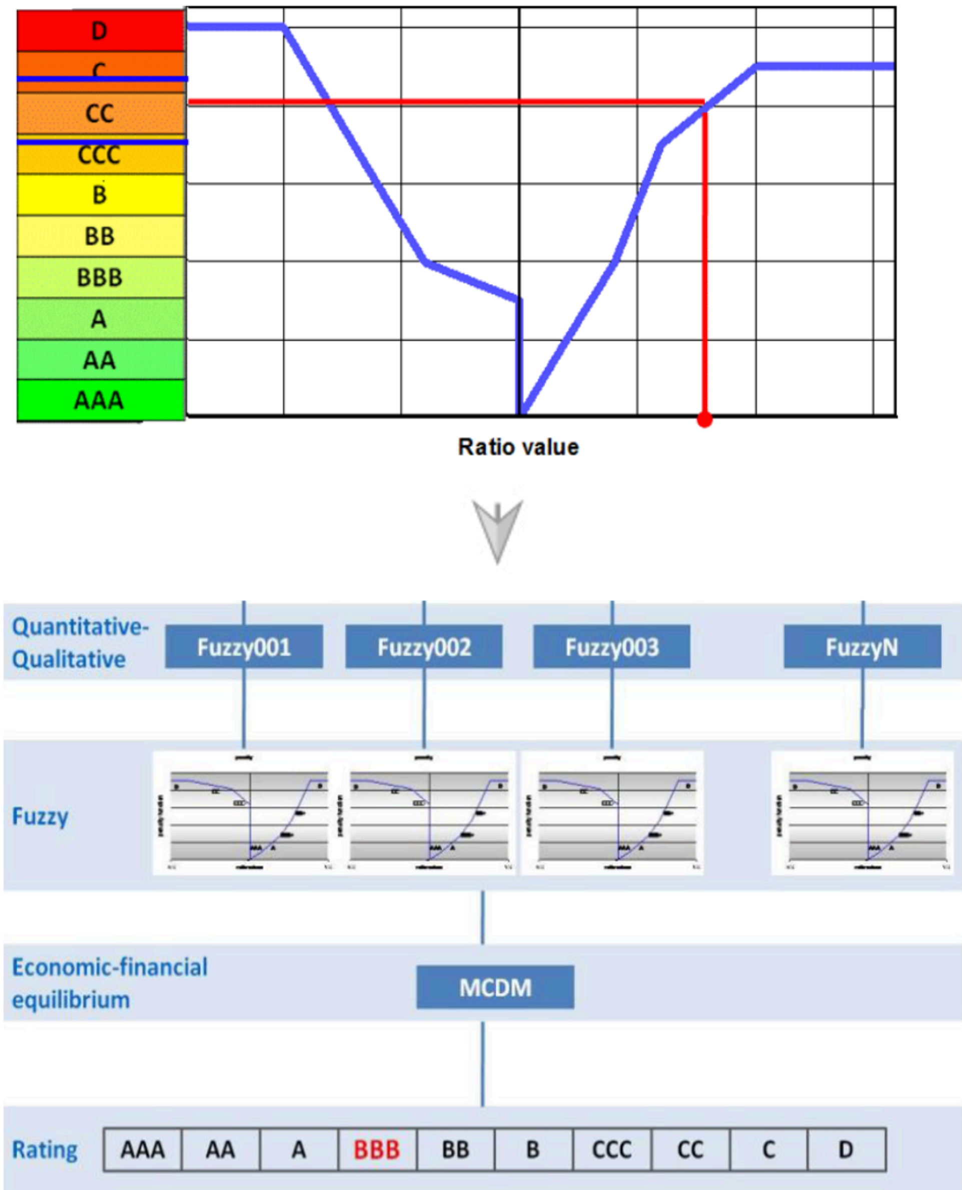
Figure 13: Representation of Fuzzy Transformation for financial ratios



Source: This figure is taken from [Internationally standardized company information for credit risk], by Bureau Van Dijk, 2017

After the determination and interpretation of the financial ratios, they are translated into a rating class obtained by using fuzzy logic. Fuzzy theory, as explained in early chapter, is a mathematical model that expresses qualitative terms into quantitative values. Fuzzy theory is used to associate each ratio to an opinion on its value meaning that it converts the numerical values (ratios) into qualitative information (rating class). *Figure 13* gives an illustration on how fuzzy transformation works which is the fundamental basis of MORE model. In the *Figure*

Figure 14: Fuzzy Logic used in Transformation of Numerical Values into Scores



Source: These figures are taken from [The Multi Objective Rating Evaluation (MORE)], by Modefinance, 2017

13, x-axis measures one financial ratio, while y-axis shows the probability of a company rated according to its given country. The peaks of each distribution of country X and country Y that falls on to x-axis display the most likely ratio of a company which is the most probable ratio given its observed data. By using the most likely ratio, the MORE model fixes the BB rating as a median of the distribution as well as fixing upper and lower ratings. In accordance with the distribution, company X gets an AA rating for its ratio because it performs better than the other companies in country X. On the other hand, company Y gets CCC rating even though company Y and company X have the same ratios. It is because company Y's ratio is worse compared to the companies in its own country, country Y (Bureau Van Dijk, 2017). *Figure 14* illustrates this transformation for each ratio. In the first figure in *Figure 14* represents the distribution of a ratio which is shown detailly in *Figure 13,* and its corresponding scores. First a score is assigned to each ratio with fuzzy transformation, and after multiple-criteria decision making tool is applied to create final MORE score.

Human Intervention

This step represents the qualitative part of credit rating process. Before analyst proceed with any analysis, some conditions need to be met:

1. The last annual account should not be older than 20 months
2. A minimum requirement needs to be met for financial figures: availability of annual accounts for the last two fiscal years or minimum requirement financial items needs to be available for last two years: Shareholder's funds, total assets, current assets, current liabilities, sales/operating revenues, EBIT and profits/losses for the period
3. Figures needs be thousands of euros, they are in different currency, analyst has to apply nearest year end foreign currency rate.
4. The main country of the rated company, its trade description and its sector activities need to be clear
5. Financial figures need to be accurate meaning no sign of error such as unbalances between total assets and total liabilities.
6. Additional guidelines for analyst: if it exists, the consolidated account is preferred and if available interim reports also need to be collected and analyzed.

After the conditions are controlled and met, the main part of human intervention is subject to assessing some of the aspects of the rated company through a set of balanced scorecards. The analyst needs to investigate these characteristics which can lead potential change in company's final rating. These assessments are classified into two main group: Company and the Group and, Industry and Country.

Company and the Group

Analyst considers the components related to the rated company and its groups. These considerations for rated entity are size, longevity, governance, legal status and group analysis. When dealing with these characteristics, analyst needs to focus on potential source of the risk emerging from these components that are not just numerical figures but textual parts of inputs such as: guarantees, business management reports etc.

Industry and Country

Analyst considers the components related to the rated company's country and its industry. Information about rated entity's industry covers the creditworthiness of the industry, the news that can potentially affect macroeconomic conditions, political risk and country. While country characteristics covers the scale of economy, GDP growth and its volatility, national income, inflation rate and its volatility, government gross debt, current account balance and political rish in which rated company operates.

Final Rating

Each outcome from the subsets of country and the group, and industry and country assign a value varies from -0.1 to 0.1. Negative value reduces the credit score and may lead to higher credit score which means less credit risk is applied to the entity and vice versa. At the end of two subsets' values are obtained. The final score from step in human intervention is the sum of these values which are added in MORE Score and creates provisional mode finance rating class which can be seen in *Figure 12* in step 5. This provisional rating is the basis for proposal of the analysts. The analyst can change the provisional rating by making adjustments in maximum one modefinance rating class to upwards or downwards or leave the rating as in the provisional. After the analyst adjustment final score is attained to company (Modefinance, 2017).

2.6 The Effects of Fintech

The financial service industry has been shaped by fintech organizations by offering new or innovative services combining the speed and flexibility, supported by forward-looking strategies, and advance business models (Nicoletti, 2017). Finance exists at the center in an economy, so the significance of financial innovations and Fintech is rising naturally for the economic growth (Frame & White, 2004). The survey of Goodwin's Fintech (2020) shows that the fintech sector has a steady grow pace and expected to grow even more in the future with the evaluation of services from data analytics to cybersecurity and will bring more opportunities as well as challenges to both investors and innovators (Dolman & Joachim, 2020). He (2017) discusses the effects of fintech on change in many structures like the barrier of entry boundaries, reliance on traditional institutions and cross border payment (He, et al., 2017) Kammoun et al. (2020) emphasizes FinTech's effects on country's economic performances together with the more efficient use of financial services and products by individuals and the small, medium and large business will lead more spending and overall growing and at the end GDP level of the country will increases (Kammoun, Loukil, & Romdhane Loukil, 2020).

Chapter 2 reviewed the theoretical information of Fintech informing its history and dimensions. Moreover, the main technologies used in credit risk evaluation is introduced together with a real case Modefinance Fintech CRA and its credit risk methodology are described.

Chapter 1 and Chapter 2 gave an insight on theoretical background of Credit Rating Agencies and Fintech. Chapter 3 will present an empirical analysis. The primary focus of this thesis is to explore the impact of FinTech on CRAs. Therefore, this thesis conducted an exploratory study in order to contribute to the existing information about the potential impact of FinTech on CRAs. Accordingly, this study aimed to answer to the research question within the scope of qualitative methodology and using the empirical data has been gathered from the individuals and professionals in the finance through the combination of survey and semi-structured interviews.

CHAPTER 3: METHODOLOGY

Chapter 3 explains the methodology of this thesis starting from presenting the main philosophy of the research. It gives the details about the surveys and interviews that conducted in order to investigate the aim of this thesis and provides summaries

3.1 Main Philosophy of The Research

A research paradigm is a philosophical scheme which show the way of doing a scientific research (Collis & Hussey, 2014). The paradigm that adapted guides researchers' investigation on data collection and procedures of the analysis (Kamal, 2019). Therefore, researchers should be able to understand and define the philosophy of their research project and the methodological attitude in order to provide a conceptual lens from their perspective to people (Kivunja & Kuyini, 2017; Rehman & Alharthi, 2016). Collis & Hussey (2014) defines two main paradigms, positivism and interpretivism, and five assumptions of these two paradigms: Ontological, epistemological, axiological, rhetorical and methodological.

3.1.1 Positivism and Interpretivism

Positivism supports that the social reality is singular and objective so the reality cannot be affected by any investigation (Collis & Hussey, 2014). In other word, if a research reflects the positivism, that research is dealing with observable social reality concluding the research with a law-like generalization (Saunders, Lewis, & Thornhill, 2009). Methodology of positivism is mostly conducted on experimentation by developing hypotheses, collecting the empirical evidence and then rejecting or accepting the hypothesis as a result of the analyses (Rehman & Alharthi, 2016). The result of the conducted research leads to the improvement of the existing theory that can be tested by another research (Saunders, Lewis, & Thornhill, 2009).

The second paradigm is interpretivism. Interpretivism supports that social reality is not objective but subjective depending on human's perceptions (Collis & Hussey, 2014). Therefore, target of interpretivism is not to develop new theories but to clarify, evaluate the subjective reasons by considering social actions (Antwi & Hamza, 2015). Its methodology is conducted with the perspective of the participants to the research rather than the researcher collecting mostly qualitative data from participants (Rehman & Alharthi, 2016). Saunders el at. (2009)

states that one of the most important philosophy of interpretivism is the researcher's adaptation to an empathetic stance on participants. Moreover, he suggested that interpretivism perspective is suitable to the research on marketing, organizational behavior and management (Saunders, Lewis, & Thornhill, 2009).

Positivism and interpretivism represent the pure forms of paradigm. The focus of this thesis is to explore the impact of FinTech on CRAs. In order to investigate this, this thesis uses two methods: survey and interviews. In analysing survey data ,descriptive statistic will be used, and hypothesis will be structured. On the other hand, for the interviews, results do not aim to make any law-like generalization or confirm any hypothesis as Saunders el at (2009) expressed. Therefore, interpretivism perspective is closer to paradigm of this thesis' research since the aim is to achieve a deeper understanding on the effect of Fintech on CRAs but also the assumptions under positivism will be also applied. In this matter, Collis & Hussey (2014) describes also a third paradigm which is named pragmatism containing the methods from two paradigms that can be used in the same study and that will be discussed next.

3.1.2 Assumptions of paradigms

Collis & Hussey (2014) defines five assumptions of paradigms: Ontological, epistemological, axiological, rhetorical, and methodological. He adds that first three assumptions are interrelated so accepting one of them presents the latter two of them along with it while the last two assumptions are complementary to the paradigm (Collis & Hussey, 2014).

The first assumption is that ontological assumption refers the type of nature of belief about the reality: is the reality singular and objective which is linked to positivism or is it socially divided into multiple realities: subjective which is linked to the interpretivism. (Rehman & Alharthi, 2016) This thesis is subject to social reality of ontological assumptions since this study is depends on the knowledge of the survey participants and interviewees.

The second assumption is epistemological assumption which is concerned how the acceptable knowledge is constituted (Saunders, Lewis, & Thornhill, 2009). Under positivism and interpretivism, the approach considers the questions respectively: is the knowledge something that can be acquired meaning that is it observable and measurable or is it something which has to be personally experienced meaning that the knowledge is acquired from subjective evidence (Collis & Hussey, 2014; Kivunja & Kuyini, 2017). In this manner, this thesis tries to have deep understandings about the future possible effects of fintech on CRAs through surveys and interview trying to understand what people and professionals think about this effect. Therefore, interpretivist view is appropriate for this thesis.

The third assumption regards axiological assumptions, which represent the philosophical approach to make decisions about the value or the right decision relating to the research (Kivunja & Kuyini, 2017). Under the positivist axiological approach, the research is conducted value-free way and researcher is independent of the data and remains objective while under interpretivism researcher is part of the type of research conducted and researcher cannot be separated so will have a subjective stance (Saunders, Lewis, & Thornhill, 2009). Axiological assumption under interpretivism is more appropriate for this thesis since the hypothesis, the question of survey and interview is structed by me as a writer of this thesis having presumption about the topic and this research. Of course, the results of the survey and the interviews will be examined objectively.

The fourth is the rhetorical assumption represents the language used in the research (Saunders, Lewis, & Thornhill, 2009). The rhetorical assumption, which is complementary the first three assumptions but also can be written that is acceptable to the supervisor or examiners (Collis & Hussey, 2014). Positivist study mainly uses formal style expressing with passive voice while interpretivist study uses the less clear format, can be written both passive or in first person (Collis & Hussey, 2014). This thesis uses mostly passive format.

Lastly, the fifth assumption is methodological which is related to the process of the research (Collis & Hussey, 2014). It represents the techniques of the data analysis and study informing researcher's choice of the method (Rehman & Alharthi, 2016). Generally, positivists are more likely to provide a methodological concept that can be measured and described focusing on more objective facts and formulated hypothesis, on the other hand, interpretivists generally use the methods that the different perceptions can be obtained by examining a small sample over a period of time (Collis & Hussey, 2014). The part 3.2 will explain in detail about the research conducted of this thesis, its process and data collection.

3.2 A General View of The Research

A research can be classified from three wide point of view: according to its application, its objective and its inquiry mode (Goundar, 2012). In this manner, a research's application differentiates between applied research done to solve an existing question, and pure research which is applied to contribute to a general knowledge rather than solving a specific question

(Collis & Hussey, 2014; Goundar, 2012). On the other hand, a research can be divided accourding to its purpose which are exploratory, descriptive and explanatory. An exploratory research tries to find out what is going on in a stuation in order to obtain a insight about it (Robson & McCartan, 2016) A descriptive research seeks to describe a situation or phenomenon providing information and describing its attitudes while explanatory attempts to explain a relationship between two aspects of a situation (Goundar, 2012). The last perspective of a research is from an inquiry mode perspective, which represents the process and approaches that adapted to a research in order to find answers to questions. These approaches are named as quantitative and qualitative researches (Goundar, 2012). Qualitative research can be defined as an approach to explore and understand the nature of a problem which is done by generally collecting and analysing qualitative data such as published texts or interviews while quantitative research refers an approach to test theories by collecting quantitative data and using statistical methods to analyse variables (Creswell, 2014; Collis & Hussey, 2014). Of course researchers can combine these methods, approaches which is called mixed methods research so researchers can collect quantitative data and analyse it qualitatively or visa versa; converting the qualitative data into the numerical codes by quantitising it (Saunders, Lewis, & Thornhill, 2009).

The main aim of this thesis is to investigate possible impact of fintech on CRAs. Since the fintech is relatively a new topic and there is no earlier study, as much as the literature scanned, on its effect to CRAs and furthermore the aim this study is to look for ideas and develop hypothesis but rather than testing and finding a specific solution to the problem, an exploratory study was used to contribute to the existing information. To explore the idea, this thesis used qualitative methodology through structured surveys with non-professionals and professionals, and semi-structured interviews with finance professionals.

In order to investigate the possible effect of fintech on CRAs, I conducted two original surveys to non-professionals and professional people, and interviews with three professionals in financial market. I started the research with collecting general opinions from non-professional people through a structured survey before narrowing down to have insights from professional people and finance professionals. The research procedure, methodology and the findings will be explained and detailed in the part 3.3.

3.3 The Three Stages of The Research

This part will explain the methods used in this thesis. Arrangement of the methods listed in this part is according to the timing and generalization of the participants. This means that the research started with a survey (stage one) in which the participant considered as non-professionals meaning that everyone regardless of having knowledge about fintech or CRAs can participate this survey. In the second survey (stage two) the participant narrowed down to professional people with an expectation that their knowledge about fintech and CRAs be more and can provide a different insight. The third and final stage is the interviews conducted with three professionals representing the three different perspectives: from someone experienced in traditional CRAs, from someone experienced in Fintech CRA and from someone who works as an investor.

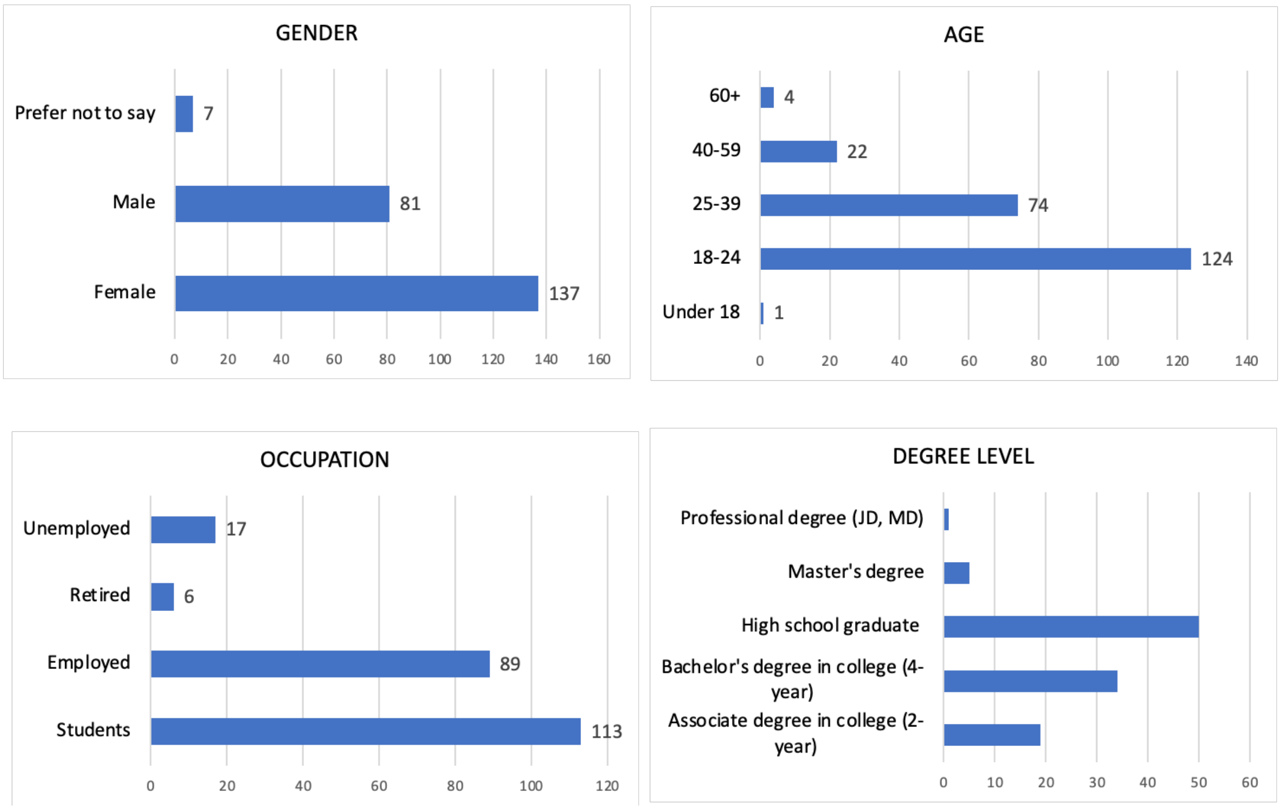
3.3.1 Survey with Non-Professionals

Purpose: The purpose of this survey is to obtain a general understanding about people's knowledge about CRAs, people attitude towards Fintech, and the ideas of effect of Fintech on CRAs, or financial institutions. The survey questions are presented in *Appendix 1*.

The Description: The survey is comprised of four blocks, for a total of 29 questions. Overall, 225 people completed the survey fully. The first block contains standard demographic questions. Graph 1 shows the summary of how people responded.

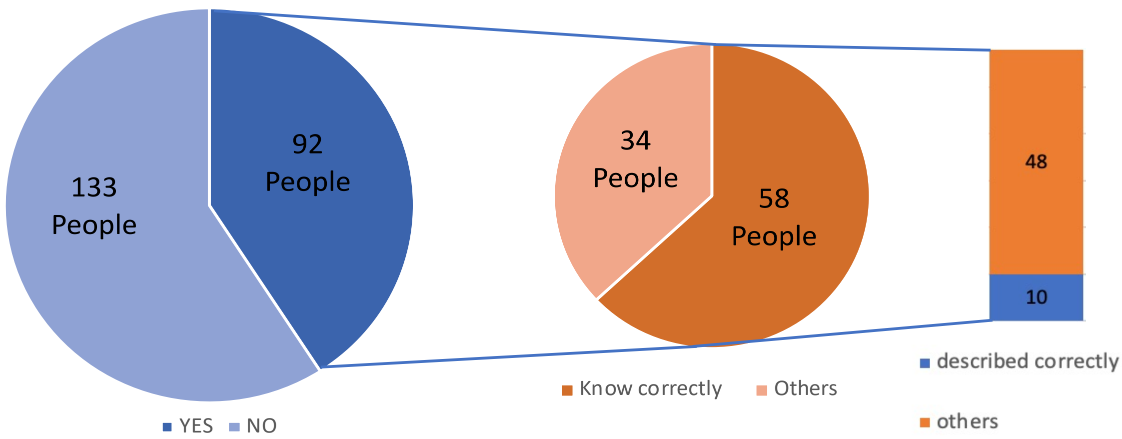
The second block contains questions to test the knowledge of CRAs and how well people know about CRAs as well as how much reliable they find the ratings from CRAs. The second block started with a question of "Do you know what a credit rating agency is?". This question directly separates the people who know and who do not know. People who say "NO" to this question do not answer any other questions on the first block considering defining CRAs in a survey is not possible and being aware that many people never even heard what a credit rating

Graph 1: Summary of Demographic Information



agency is. On the other hand, people who selected as "YES" to that question are shown and answer also to other questions related to CRAs. The second and third questions are designed to understand if the people who said "YES" really know what a CRA is and what really a CRA does. According to the results of this answer, a distinction can be made between people who think they know what a CRA is but really their knowledge is nothing more than a familiarity. Graph 2 shows the result how many people do not know, know or they think they know. As it can be seen in the Graph 2, 133 people out of 225 responders answered "YES" to the question of "Do you know what a credit rating agency is?", while 58 people out of 92 answered correctly to the question of which company is a CRA. Moreover 10 people out of 58 people chose the correct option for the description of CRAs

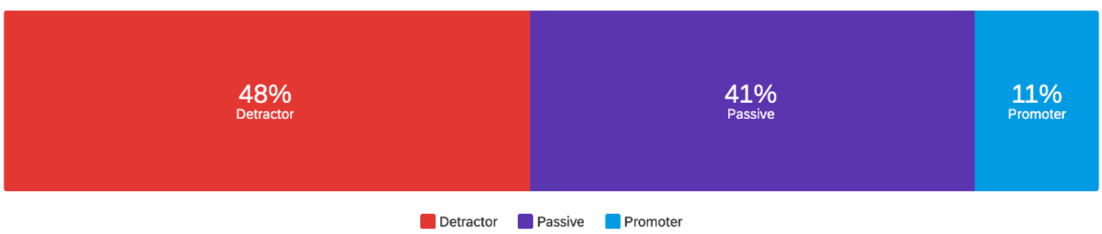
Graph 2: Knowledge of CRA



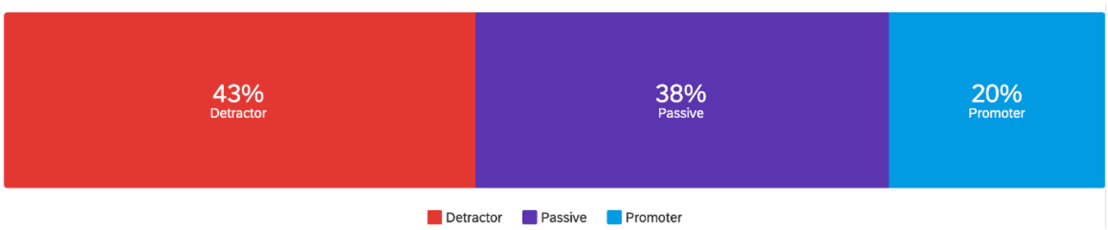
The third block contains questions about technology and fintech. The purpose of the third block is to understand how important the technology and fintech for people who responded and how much reliable people find fintech services and technology. *Graph 3* provides summary scale result for the written questions. Promoter represents the responders who scored between 9-10, while detractor represents the responders who scored between 0 and 6. In this scale 10 represents the people who trust the technology extremely and find using fintech services extremely safe, while 0 represents the other way around.

Graph 3: Fintech Block

How much do you trust the technology?



How safe do you think to use Fintech services?



The fourth and last block contain questions to understand people's preferences between fintech and traditional methods. Moreover, it contains our main research question on what people foresee for the future adaptation of fintech and CRAs.

Descriptive Statistics and Inferential Statistics: Descriptive statistics enable researchers to describe and compare the variables in the research conducted numerically (Saunders, Lewis, & Thornhill, 2009). As explained earlier, a survey was conducted among non-professionals, and the summary of the key participants's characteristics and answers was explained in *The Description* part above. In this part, I want to examine more in depth the results by looking the relationships between the variables to see how related the variables are and if there is any relationship. First a descriptive statistic will be used in order to distinguish the patterns that are not very visible in summary of raw data after, an inferential statistic will be performed that help me to lead a draw a conclusion from the data collected from survey (Collis & Hussey, 2014). This process is also known as significance or hypothesis testing which enables to compare the data with what theoretically is expected to happen, and what result is founded (Saunders, Lewis, & Thornhill, 2009). There are two main statistics tests: parametric and non-parametric. Parametric tests are used with numerical data that should comply number of assumptions while non-parametric data is used generally with not normally distributed, categorical data (Saunders, Lewis, & Thornhill, 2009).

The hypothesis I built will guide me to determine the appropriate test needs to be conducted. Therefore, I will go hypothesis by hypothesis. The null hypotheses are shown as Ho, while the alternative hypotheses are presented as H_a. Nevertheless, before presenting any results, the tests I used in this thesis will be explained. These tests are Mann-Whitney and Kruskal Wallis tests and Chi-square test. I used excel and RStudio tools for analysis.

Mann-Whitney and Kruskal Wallis test

Mann-Whitney (MW) test is a statistical test that used to evaluate the likelihood of any difference between two groups (Saunders, Lewis, & Thornhill, 2009). This test is used if a researcher is dealing with non-parametric data on quantile scale as independent variable and having two sample of dependent variable to conclude whether there is a difference between these two samples (Collis & Hussey, 2014). On the other hand, Kruskal Wallis (KW) test is described as an extension of the Mann-Whitney test meaning that it is again a non-parametric test of statistical significant but it is used when testing three or more independent samples (Fay, 2006). There are three main assumptions for Mann-Whitney and Kruskal Wallis test (Nachar, 2008):

1. The investigated groups must be randomly drawn from the population
2. There should be independence between the observations meaning that each has to belong to a different participant
3. The observation values should be measured with ordinal or continuous type.

Chi-square Test

Chi-square test is a statistical test to determine likelihood two variables whether they are associated or not (Saunders, Lewis, & Thornhill, 2009). It is a non-parametric test for two variables that are measured on a nominal scale (Collis & Hussey, 2014).

Shapiro-Wilk Test

Shapiro-Wilk (SW) test is a statistical test that is used to decide if the variables are normally distributed. Non-parametric tests are also called distribution-free tests, and it is considered more powerful tests for the data that are not normally distributed. Therefore, Shapiro-wilk test is used in order to confirm that the sample of data is not normally distributed, so that non-parametric test can be applied. The hypothesis for this test is as follows:

H_0: Data are normally distributed.

H_1: Data are not normally distributed.

TEST 1

Respondents were asked scale their trust to technology from 0 to 10. *Figure A.1* provides the descriptive statistics. The summary shows that the data has around 2.23 standard deviation with 7 median and 6.298 mean. Moreover, the histogram shows that the distribution of male and female by level of trust to technology have a similar pattern and negatively skewed so that they are not

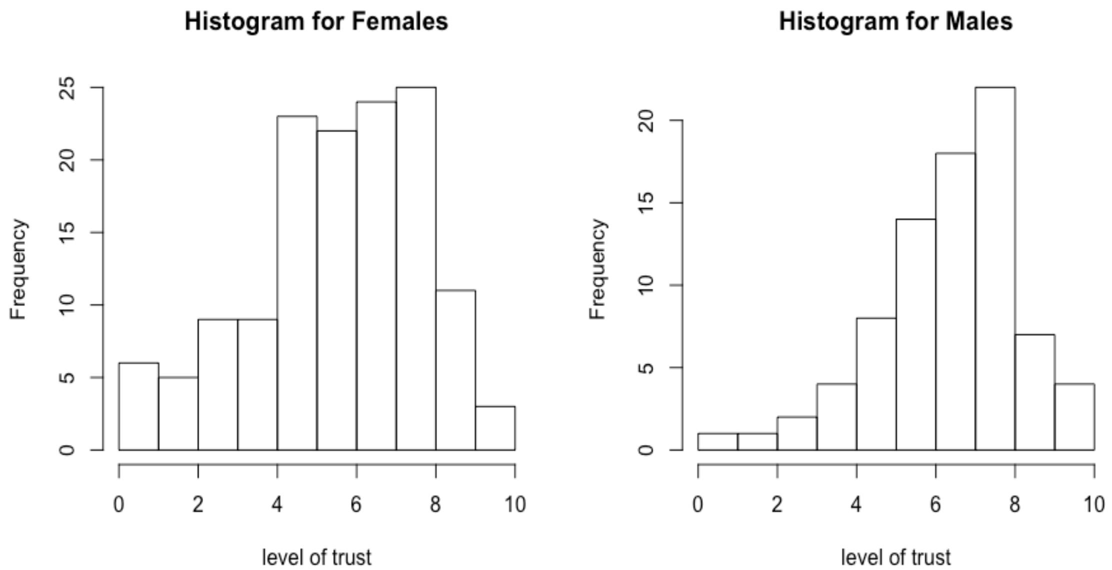
Figure A.1

Count of GENDER	Column Labels											
Row Labels	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Grand Total**
Female	3	3	5	9	9	23	22	24	25	11	3	137
Male	1		1	2	4	8	14	18	22	7	4	81
Grand Total	**4**	**3**	**6**	**11**	**13**	**31**	**36**	**42**	**47**	**18**	**7**	**218**

	Male	Female	Total
std	2,2261329	1,84248557	2,12687
median	6	7	7
mean	5,98540146	6,82716049	6,29816514

normally distributed, also SW confirmed that by rejecting null hypothesis of data are normally distributed. Both histogram and SW test can be seen in *Figure A.2.* The median scores show that trust level for each degree having highest is the females while lowest is males.

Figure A.2




```
Shapiro-Wilk normality test

data:  H1$GENDER
W = 0.61199, p-value < 2.2e-16
```

For this hypothesis, MW test is applied with the null and alternative hypothesis:

H0: The level of trust does not differentiate based on gender

H1: The level of trust differs based on gender

As a result of the test, it can be seen in *Figure A.3,* p-value shows that the difference between two variables is statistically significant since p-value is lower than 0.05. Therefore, null hypothesis of "The level of trust does not differentiate based on gender" can be rejected.

Figure A.3

```
	Wilcoxon rank sum test with continuity correction

data:  H1$GENDER and H1$TECHTRUST
W = 1563.5, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

TEST 2

Respondents were asked scale their trust to fintech services from 0 to 10. *Figure B.1* provides the descriptive statistics. The summary shows that the data has around 2.13 standard deviation with 7 median and 6.75 mean. The median scores show that trust level for each degree having highest is the participants who have master's degree while lowest is people who has high school degree. Moreover, the histogram and SW test show that the data are not normally distributed. Both histogram and SW test can be seen in *Figure B.2.*

Figure B.1

Count of DEGREE LEVEL												
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
Bachelor's degree in college (4-year)		3		2	8	13	15	16	20	12	11	100
High school graduate	1	1		2	4	13	8	8	9	5	4	55
Associate degree in college (2-year)	1		1	1	3	7	2	4	7		5	31
Master's degree					1	1	3	7	9	4	3	28
Doctoral degree				1		2		2	1	1		7
Professional degree (JD, MD)						1			1			2
Less than high school degree								1				1
Total	**2**	**4**	**1**	**6**	**16**	**37**	**28**	**38**	**47**	**22**	**23**	**224**

MEDIAN **POPULATION**

```
HighSchool two-yeardegree bachelordegree   masterdegree            PHd
         6               7              7              8              7     7
```

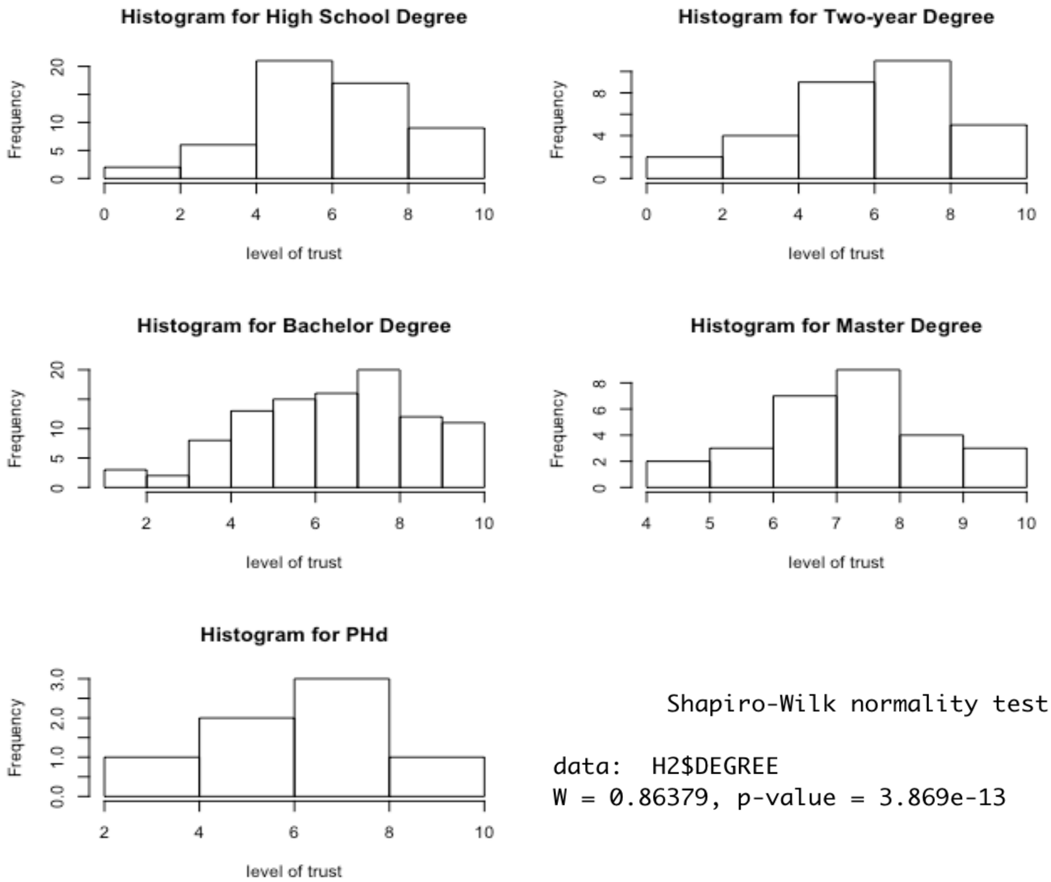
MEAN

```
HighSchool two-yeardegree bachelordegree   masterdegree            PHd
  6.345455        6.387097       6.860000       7.642857       6.285714    6.746606
```

Std

```
HighSchool two-yeardegree bachelordegree   masterdegree            PHd
  2.170665        2.499032       2.117841       1.445665       2.058663    2.138192
```

Figure B.2




```
        Shapiro-Wilk normality test

data:  H2$DEGREE
W = 0.86379, p-value = 3.869e-13
```

For this hypothesis, MW test is applied with the null and alternative hypothesis:

H0: The level of trust does not differentiate based on degree level

H2: The level of trust differs based on degree level

As a result of the KW test, it can be seen in *Figure B.3,* p-value shows that the difference between variables is not statistically significant since p-value is higher than 0.05. Therefore, null hypothesis of "The level of trust does not differentiate based on degree level" cannot be rejected.

Figure B.3

```
        Kruskal-Wallis rank sum test

data:  H2$FINTRUST by H2$DEGREE
Kruskal-Wallis chi-squared = 8.4733, df = 4, p-value = 0.0757
```

TEST 3

Respondents were asked to choose one of the options of “I would prefer to rely on a software analyzing regarding this person's creditworthiness” and “I would prefer to rely on an expert's opinion by a real professional regarding this person's creditworthiness” to the question of “Which of the following options would you use to determine this person's ability to repay the debt you borrowed”. 102 participants out of 213 chose to rely on software while 111 out of 213 participant selected expert’s opinion. Shapiro-Wilk test confirms that variables are not normally distributed. *Figure C.1* provides the summary.

Figure a.1

	Rely on expert	Rely on software	Grand Total
Bachelor's degree in college (4-year)	47	53	100
High school graduate	33	22	55
Associate degree in college (2-year)	18	12	30
Master's degree	13	15	28
Grand Total	**111**	**102**	**213**

```
Shapiro-Wilk normality test

data:  H3$THECHOISE
W = 0.63579, p-value < 2.2e-16
```

For this hypothesis, KW test is applied with the null and alternative hypothesis:

H0: The choice does not differentiate based on degree level

H3: The choice differs based on degree level

As a result of the test, it can be seen in *Figure C.2,* p-value shows that the difference between variables is not statistically significant since p-value is higher than 0.05. Therefore, null hypothesis of “The choice does not differentiate based on degree level” cannot be rejected.

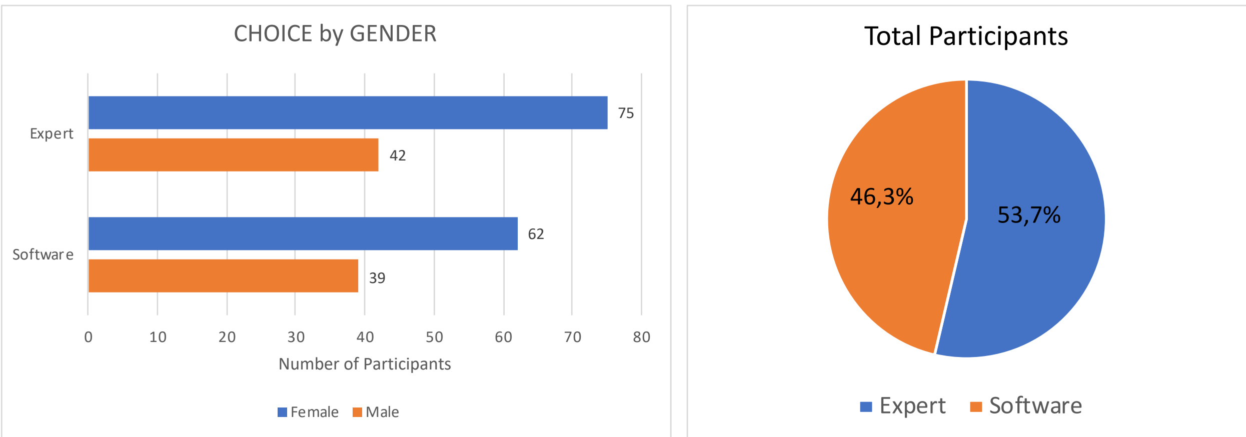
Figure C.2

```
        Kruskal-Wallis rank sum test

data:  H3$THECHOISE by H3$DEGREELEVEL
Kruskal-Wallis chi-squared = 3.5123, df = 3, p-value = 0.3192
```

TEST 4

Respondents were asked to choose one of the options of “I would prefer to rely on a software analyzing regarding this person's creditworthiness” and “I would prefer to rely on an expert's opinion by a real professional regarding this person's creditworthiness” to the question of “Which of the following options would you use to determine this person's ability to repay the debt you borrowed”. 46.3% participant relied on software’s decision while 53.7% did on expert’s opinion. The summary is shown in *Figure D.1*.

Figure D.1



For this hypothesis, chi-squared test is applied with the null and alternative hypothesis:

H0: The choice does not differentiate based on gender

H4: The choice differs based on gender

As a result of the test, it can be seen in *Figure D.2,* p-value shows that the difference between variables is not statistically significant since p-value is higher than 0.05. Therefore, null hypothesis of “The choice does not differentiate based on gender” cannot be rejected.

Figure D.2

```
        Pearson's Chi-squared test with Yates' continuity correction

data:  H4$GENDER and H4$CHOICE2
X-squared = 0.074716, df = 1, p-value = 0.7846
```

TEST 5

Respondents were asked whether they know what a CRA is or not. I sorted the data as employed and students. 127 participants out of 208 selected “NO” representing they do not know, while 95 participants selected “YES”.

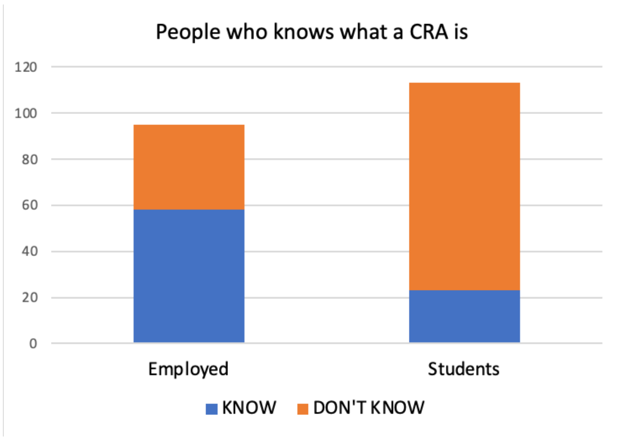
For this hypothesis, chi-squared test is applied with the null and alternative hypothesis:

H0: Knowledge of CRA is not related to the occupation

H4: Knowledge of CRA is related to the occupation

As a result of the test, it can be seen in *Figure E.1* which also provides summary of participants, p-value shows that the difference between variables is statistically significant since p-value is lower than 0.05. Therefore, null hypothesis of “Knowledge of CRA is not related to the occupation” can be rejected.

Figure E.1



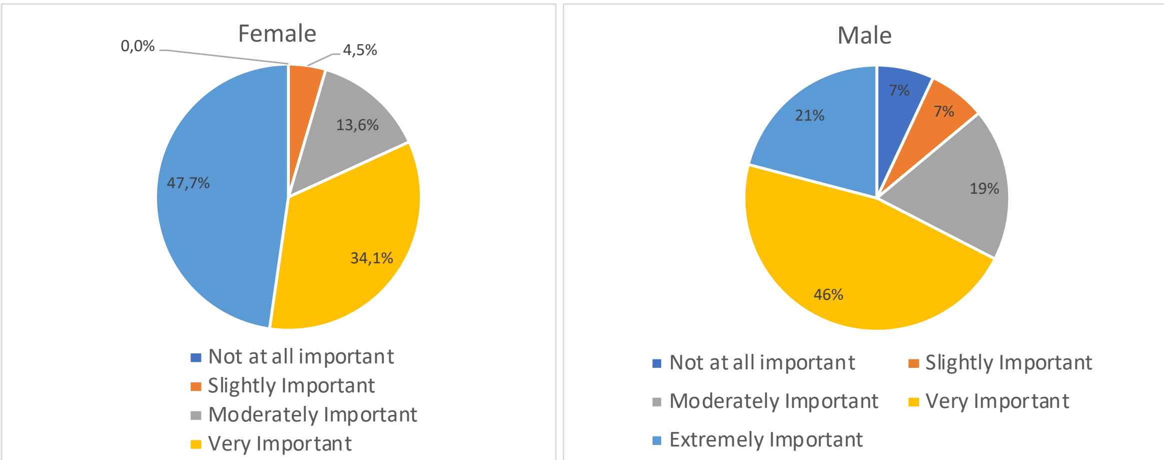

```
   OCCUPATION   KNOWLEDGE
employed: 95    NO :127
student :113    YES: 81
```

```
        Pearson's Chi-squared test

data:  OCCUPATION and KNOWLEDGE
X-squared = 35.953, df = 1, p-value = 2.021e-09
```

TEST 6

Respondents who know what a CRA were asked how important they find the CRAs? The answers have five scale starting from “Extremely Important”, to “Not at all Important”. *Figure F.1* provides the descriptive statistics. The summary shows that the data has around 1.03 standard deviation with 4 median and 3.97 mean. Moreover, the histogram shows that the distribution of male and female by level of importance of CRA have a similar pattern and negatively skewed so that they are not normally distributed, also SW approved that by rejecting null hypothesis of data are not normally distributed. Both histogram and SW test can be seen in *Figure F.2*.

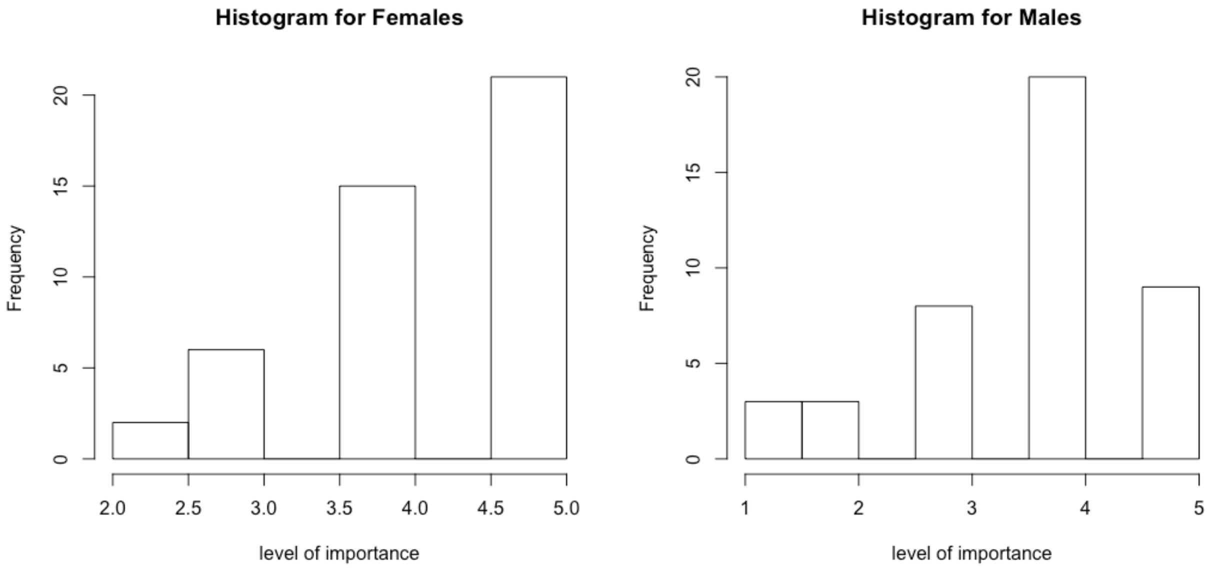
Figure F.1



Row Labels	Not at all important	Extremely important	Moderately important	Slightly important	Very important	Grand Total
Female		21	6	2	15	44
Male	3	9	8	3	20	43
Grand Total	**3**	**30**	**14**	**5**	**35**	**87**

	Male	Female	Total
std	1,10670963	0,8660254	1,02807
median	4	4	4
mean	3,6744186	4,25	3,96551724

Figure F.2




```
        Shapiro-Wilk normality test

data:  H6.1$GENDER
W = 0.63638, p-value = 2.338e-13
```

For this hypothesis, MW test is applied with the null and alternative hypothesis:

H0: The Level of Importance of CRA is not related to the gender

H6: The Level of Importance of CRA is related to the gender

As a result of the test, it can be seen in *Figure F.3,* p-value shows that the difference between two variables is statistically significant since p-value is lower than 0.05. Therefore, null hypothesis of "The Level of Importance of CRA is not related to the gender" can be rejected.

Figure F.3

```
        Wilcoxon rank sum test with continuity correction

data:  H6.1$GENDER and H6.1$IMPORTANCELEVEL
W = 302.5, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

It is important to note that in this data the medians are same. Mann-Whitney test is commonly known as a test for differences in medians (Campbell, 2009). Campbell (2009) states that two groups can have same medians but significant MW test, furthermore, he explains that if the groups have same distribution, then medians and means will be moved by the shift in location so that the difference in medians will be equal to the difference in mean, as a result MW test is also a test for mean's differences.

TEST 7

Respondents who know what CRA is, were asked how reliable they find CRAs, scaling from 0 to 10. *Figure G.1* provides the descriptive statistics. The summary shows that the data has around 1.82 standard deviation with 7 median and 6.26 mean. Moreover, the histogram shows that the distribution of employed and unemployed have a similar pattern and negatively skewed so that they are not normally distributed, also SW approved that by rejecting null hypothesis of data are normally distributed. Both histogram and SW test can be seen in *Figure G.2.* The median scores show that highest trust level for finding CRAs reliable is the females while lowest is males.

Figure G.1

Row Labels	**0**	**1**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Grand Total**
Employed	1	1	0	0	11	9	13	16	0	2	53
Unemployed	1	0	3	3	6	6	10	4	0	0	33
Grand Total	**2**	**1**	**3**	**3**	**17**	**15**	**23**	**20**	**2**	**2**	**86**

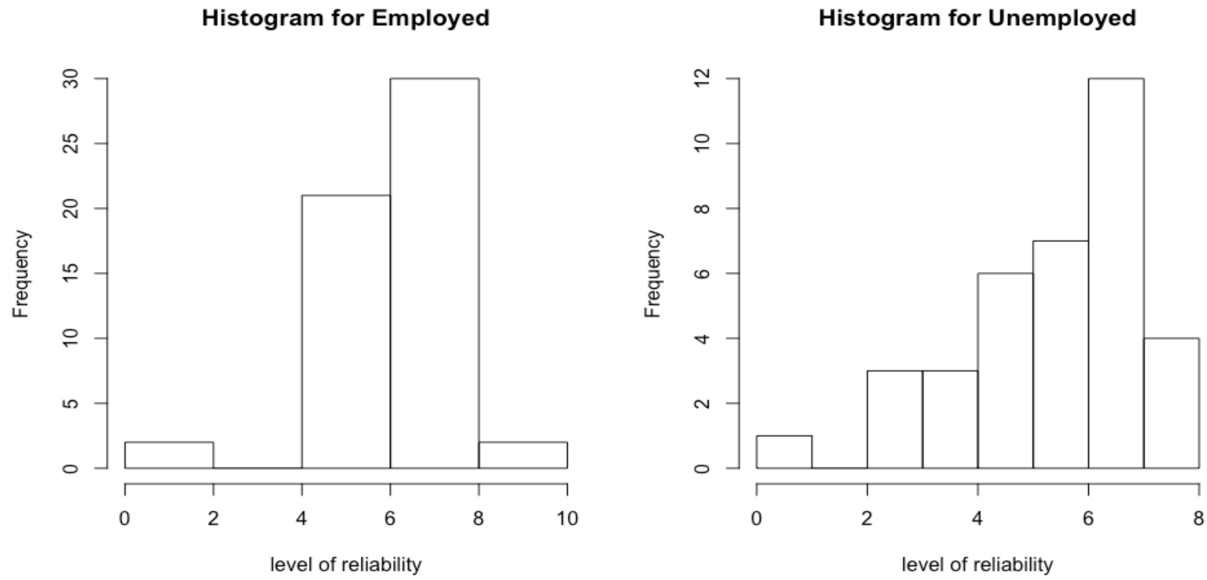
	Employed	**Unemployed**	**Total**
std	1,76976707	1,807497014	1,82264
median	7	6	7
mean	6,58490566	5,727272727	6,255813953

For this hypothesis, MW test is applied with the null and alternative hypothesis:

H0: The Level of Reliability of CRA is not related to the occupation

H7: The Level of Reliability of CRA is related to the occupation

Figure G.2




```
                    Shapiro-Wilk normality test

data:  H7$OCCUP
W = 0.62037, p-value = 5.444e-14
```

As a result of the test, it can be seen in *Figure G.3,* p-value shows that the difference between two variables is statistically significant since p-value is lower than 0.05. Therefore, null hypothesis of “The Level of Reliability of CRA is not related to the occupation” can be rejected.

Figure G.3

```
        Wilcoxon rank sum test with continuity correction

data:  H7$OCCUP and H7$RELIAB
W = 245.5, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

TEST 8 – TEST 9

Respondents who know what a CRA is, were asked to select one of the three options to the question of "How do you think that CRAs and Fintech companies might interact?". 46% of the participants thinks that fintech companies will be acquired by CRAs while 43% of participants thinks that fintech companies will replace CRAs, and 11% of participants foresees that fintech companies remain insignificant compared to CRAs. The summary result can be seen in *Figure I.1 and Figure I.2.*

Figure I.1

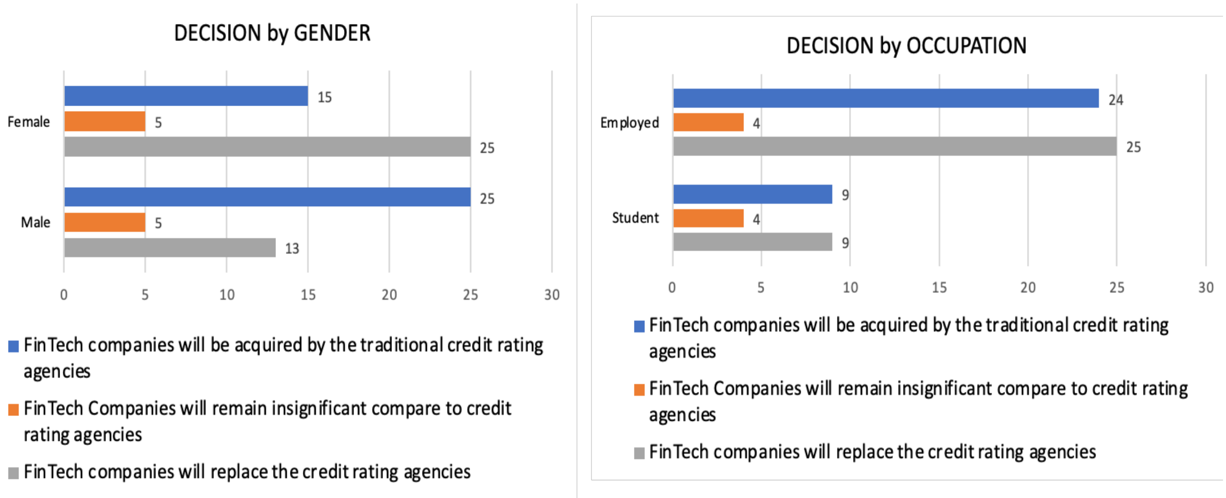
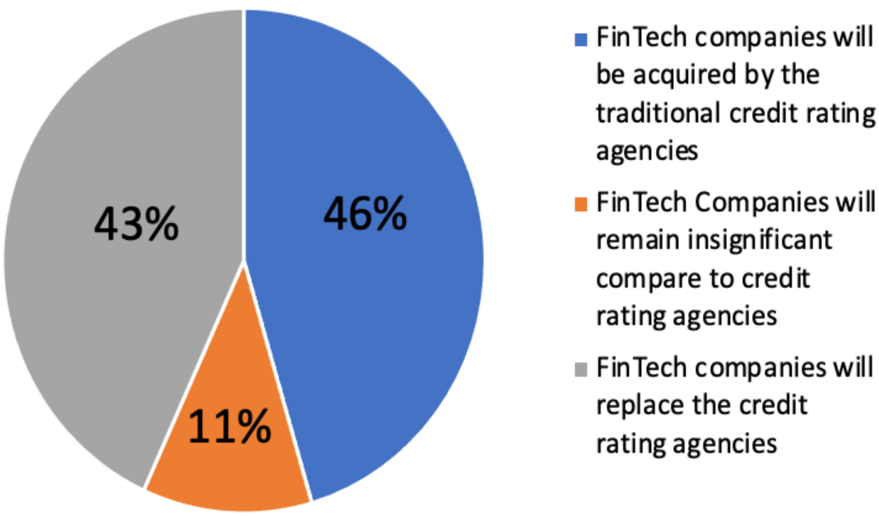


Figure I.2



Two different hypotheses were built, and chi-squared test is applied to each with the null and alternative hypothesis:

Test 8:

H0: The choice does not differentiate based on gender

H8: The choice differs based on gender

Figure I.3: Result of TEST 8

```
        Pearson's Chi-squared test

data:  H8$GENDER and H8$DECISION
X-squared = 6.2472, df = 2, p-value = 0.044
```

Test 9:

H0: The choice does not differentiate based on occupation

H9: The choice differs based on occupation

Figure I.4: Result of TEST 9

```
        Pearson's Chi-squared test

data:  H9$OCCUPA and H9$DECISION
X-squared = 1.8504, df = 2, p-value = 0.3965
```

The result of the first test indicates that, it can be seen in *Figure I.3,* p-value shows that the difference between variables is statistically significant since p-value is lower than 0.05. Therefore, null hypothesis of “The choice does not differentiate based on gender” can be rejected. On the other hand, second result of the test shows that, can be seen in *Figure I.4, its p-value is higher than 0.05 so* null hypothesis of “The choice does not differentiate based on occupation” cannot be rejected.

Summary: I built in total nine hypotheses for the survey of non-professionals. The *Table 5* summarizes the hypotheses, which tests were used, results of the tests and meaning of the results.

In the end, we show that there is a significant relationship between the employed and unemployed which are the student for the knowledge of the CRAs. Considering the term of CRA and Fintech companies are more professional terms, moreover as a result of Test 5, knowledge of CRA differentiates between the occupation, I decided to conduct a second survey for professionals which will be discussed in the part 3.3.2 Survey with Professionals.

Table 5: Summary of Hypothesis

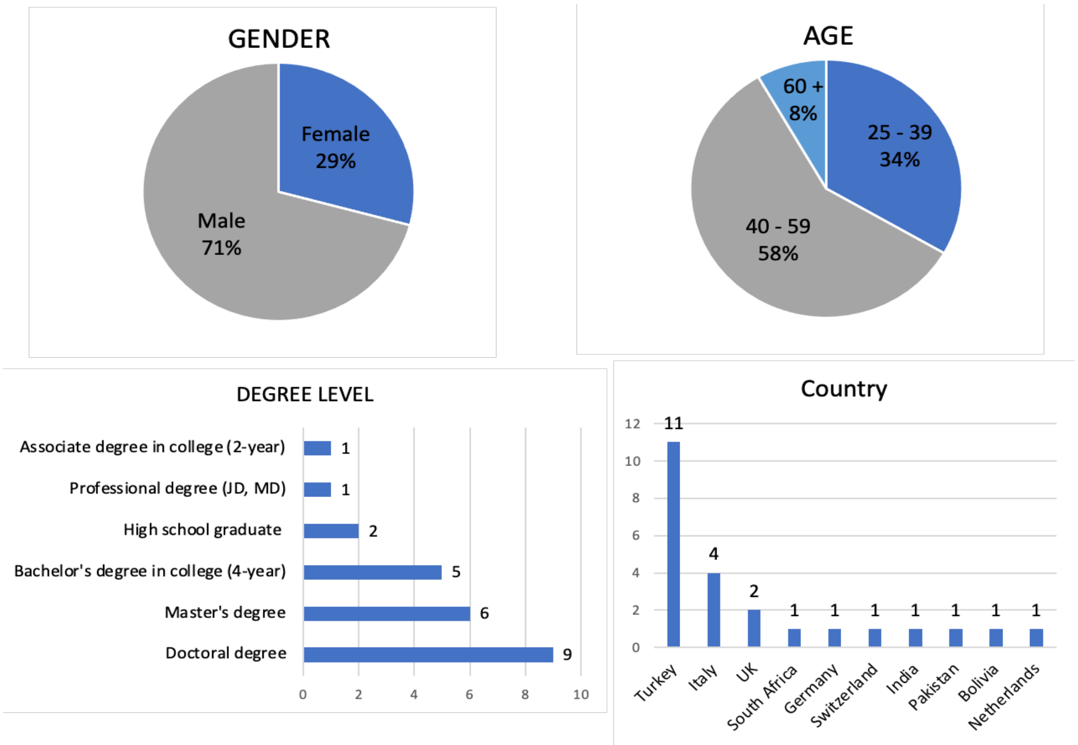
	HYPOTHESIS	TEST	RESULT	MEANING
TEST 1	H0: The level of trust does not differentiate based on gender H1: The level of trust differs based on gender	MW	Reject Null	Relationship Observed
TEST 2	H0: The level of trust does not differentiate based on degree level H2: The level of trust differs based on degree level	KW	Don't Reject Null	No Relationship
TEST 3	H0: The choice does not differentiate based on degree level H3: The choice differs based on degree level	KW	Don't Reject Null	No Relationship
TEST 4	H0: The choice does not differentiate based on gender H4: The choice differs based on gender	Chi Squared	Don't Reject Null	No Relationship
TEST 5	H0: Knowledge of CRA is not related to the occupation H5: Knowledge of CRA is related to the occupation	Chi Squared	Reject Null	Relationship Observed
TEST 6	H0: The Level of Importance of CRA is not related to the gender H6: The Level of Importance of CRA is related to the gender	MW	Reject Null	Relationship Observed
TEST 7	H0: The Level of Reliability of CRA is not related to the occupation H7: The Level of Reliability of CRA is related to the occupation	MW	Reject Null	Relationship Observed
TEST 8	H0: The choice does not differentiate based on gender H8: The choice differs based on gender	Chi Squared	Reject Null	Relationship Observed
TEST 9	H0: The choice does not differentiate based on occupation H9: The choice differs based on occupation	Chi Squared	Don't Reject Null	No Relationship

3.3.2 Survey with Professionals

Purpose: The purpose of this survey is to obtain a general understanding about professional people's opinion about CRAs, attitude towards Fintech, and the effect of Fintech on CRAs, or financial institutions. The survey questions are presented in *Appendix 2*.

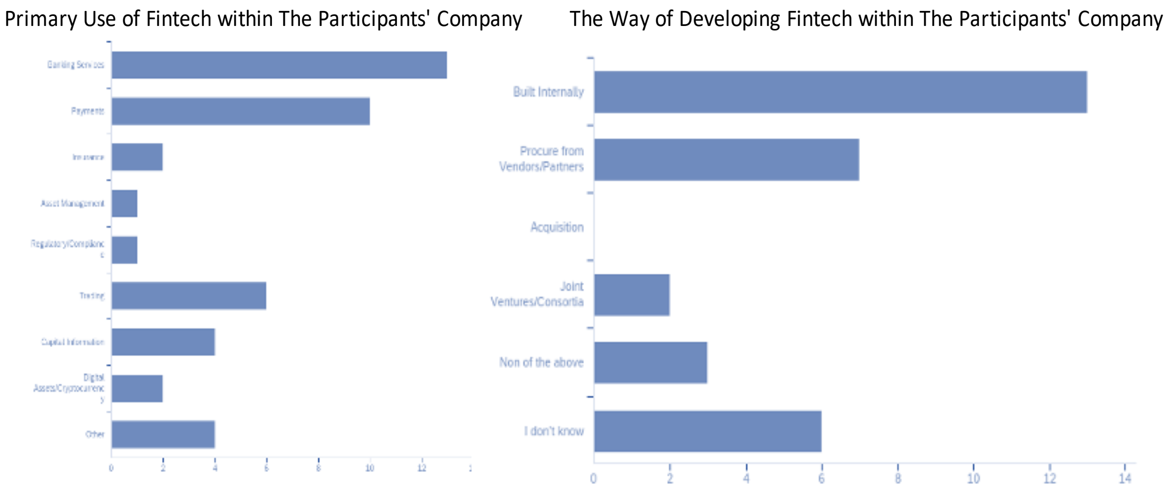
The Description: The survey is comprised of four blocks, and a total of 22 questions. In total 24 employed people completed the survey fully. The first block contains standard demographic questions. *Graph 4* shows the summary of people responded.

Graph 4

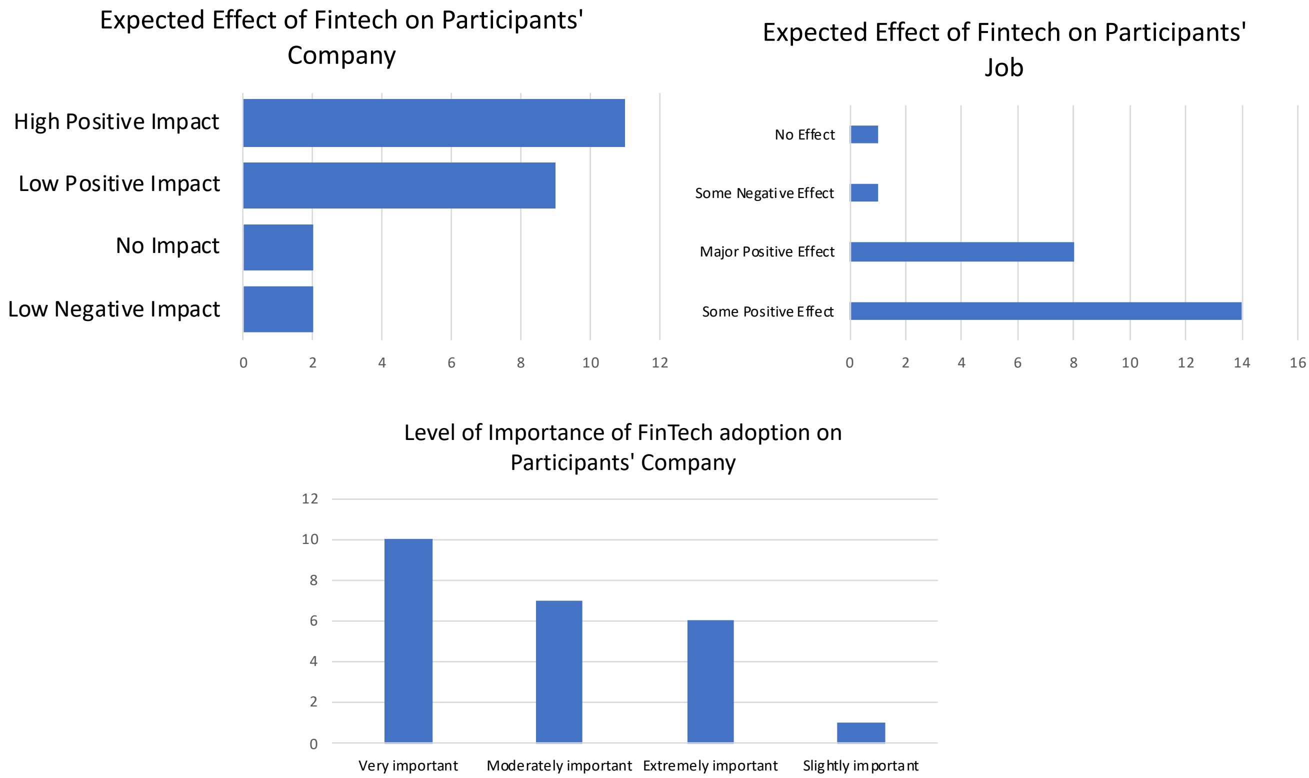


The second block contains questions about fintech. The purpose of the second block is to understand how participants' approach to fintech; how they think it affects them, how is the adaptation of fintech within their workplace and how the company in which they work use the fintech. As it can be seen in *Graph 5,* the Banking and Payment services are the primary uses of Fintech while Fintech is built mostly internally. *Graph 6* shows how the participants' company

Graph 5



Graph 6

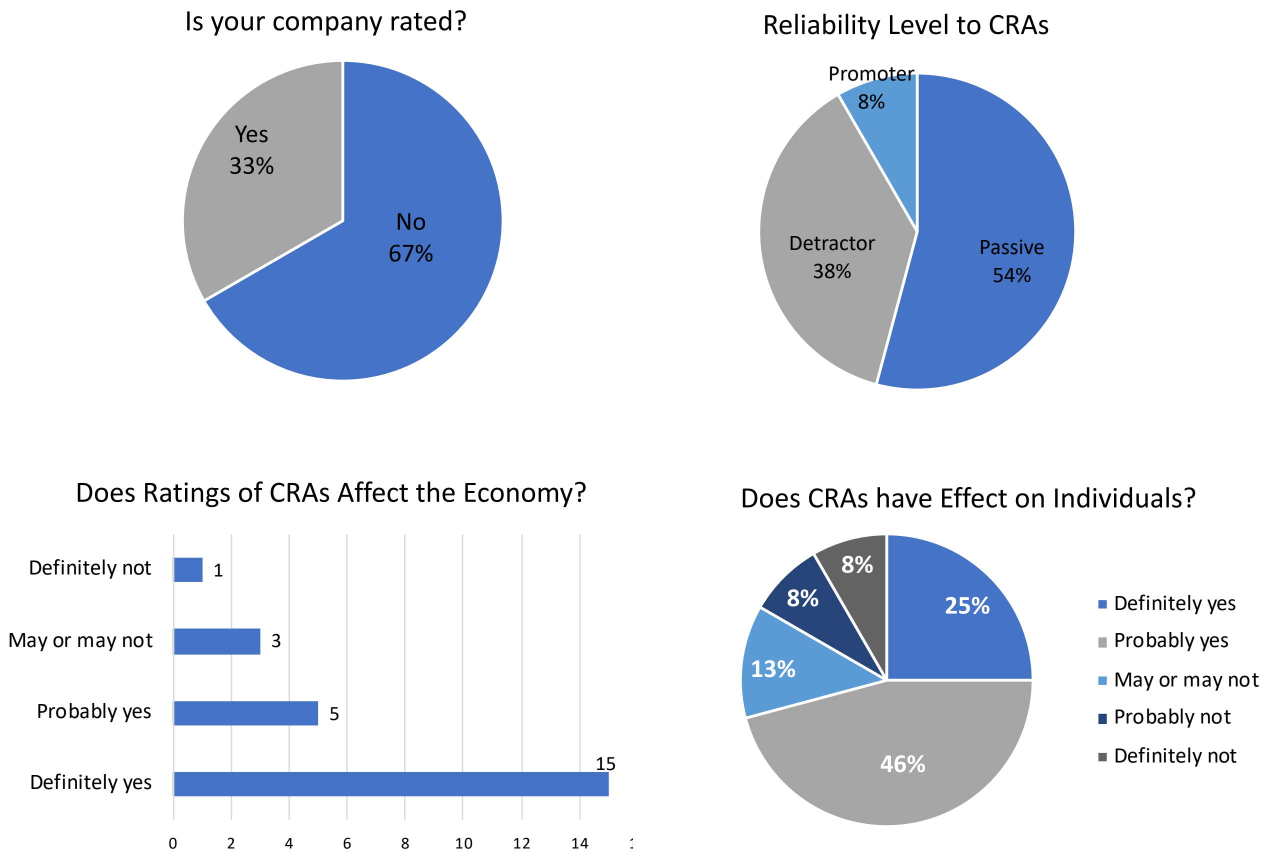


using and developing fintech while *Graph 7* provides summary result for the second block. The *Graph 7* shows that fintech mostly have a positive impact on participants' jobs and their companies while adaptation of fintech in the company is also observed important.

The third block contains questions about CRAs; how the companies in which participants work, are affected by ratings, participants' opinion about the effect of ratings, and how reliable they find the CRAs? *Graph 8* provides summary of the results. As it can be seen in the *Graph 8,* most of the participants strongly think that CRAs have affected the economy while only 25% of the participant strongly think that CRAs affect individuals. Moreover 38% of the participants finds CRAs liability low (people who scored between 0-6) while only 8% finds CRAs highly reliable.

The fourth and last block contains questions to understand participants' opinion to integration of fintech into financial institutions and CRAs. Moreover, it contains our main research question on what people foresee for the future adaptation of fintech and CRAs.

Graph 7



Descriptive Statistics and Inferential Statistics: An original survey was conducted among professionals, and the summary of the participants explained in *The Description* part above. In this part, I want to examine more in debt of the result by looking the relationships between the variables to see how related the variables are and if there is any relationship. First a descriptive statistic will be presented after an inferential statistic will be performed.

This part the hypothesis I built will guide me to determine the appropriate test needs to be conducted. Therefore, I will go hypothesis by hypothesis. The null hypotheses are shown as Ho, while the alternative hypotheses are presented as H_a. I used excel and RStudio tools for analyses.

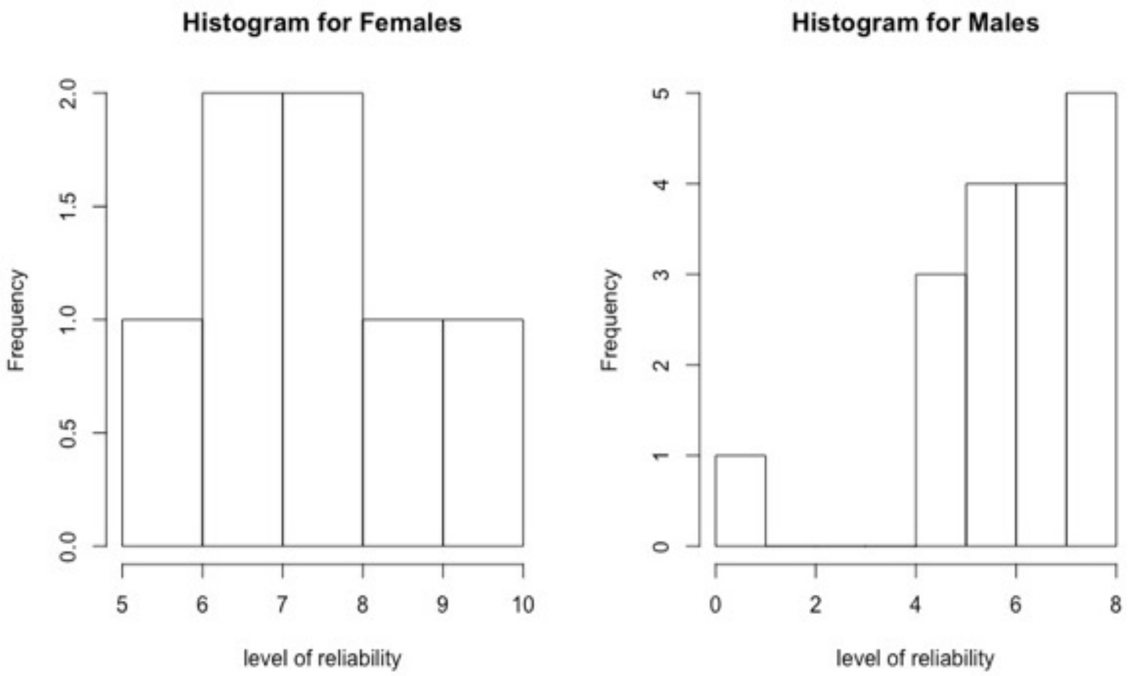
TEST 1 – TEST 2

Respondents were asked scale how reliable they find CRAs. *Figure a.1* provides the descriptive statistics related to degree levels and gender. The summary shows that the data has around 1.27 and 1.94 standard deviations with 7 and 7 medians and 6.85 and 7,71 means by degree levels and genders respectively. Moreover, in *Figure a.2,* the histograms show the distributions of three different degree levels and gender by level of reliability to CRAs, which are not normal, and SW approved these by rejecting null hypothesis of data are normally distributed. The median scores show that trust level for each degree levels. It can be seen that the participants that have bachelor's degree from the test 1 and female participants from test two are presenting the highest trust to CRAs while participants having master's degree and male participants presenting the lowest trust to CRAs.

Figure a.1

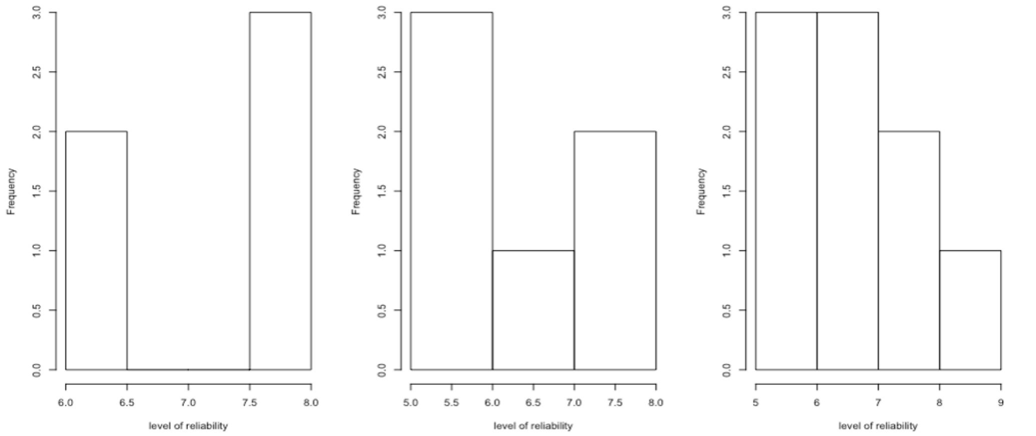
	Bachelor Degree	Master's Degree	PHd	Total
std	1,095	1,378	1,364	1,268
median	8	6,5	7	7
mean	7,200	6,500	6,889	6,850
Number of Observant	5	6	9	6,85

	Female	Male	Total
std	1,604	1,961	1,944
median	8	7	7
mean	7,714	6,294	6,708
Number of Observant	7	17	24




```
Shapiro-Wilk normality test

data:  H2$GENDER
W = 0.57334, p-value = 3.156e-07
```

Figure a.2




```
            Shapiro-Wilk normality test

data:  H1$DEGREELEVEL
W = 0.77774, p-value = 0.0004099
```

For Test 1 hypothesis, KW test is applied with the null and alternative hypothesis:

H0: The level of reliability of CRA is not related to degree level

H1: The level of reliability of CRA is related to degree level

For Test 2 hypothesis, MW test is applied with the null and alternative hypothesis:

H0: The level of reliability of CRA is not related to gender

H2: The level of reliability of CRA is related to gender

As a result of the tests, it can be seen in *Figure a.3,* p-value for test 1 shows that the difference between two variables is not statistically significant since p-value is higher than 0.05., Therefore, null hypothesis of "The level of reliability of CRA is not related to degree level" cannot be rejected. On the other hand, p-value for test 2 indicates that we cannot reject null hypothesis of "The level of reliability of CRA is not related to gender" because p-value is lower than 0.05.

Figure a.3

```
        Kruskal-Wallis rank sum test

data:  H1$CRALEVELRELIABLE by H1$DEGREELEVEL
Kruskal-Wallis chi-squared = 0.85463, df = 2, p-value = 0.6523


        Wilcoxon rank sum test with continuity correction

data:  H2$GENDER and H2$CRALEVELRELIAB
W = 24, p-value = 2.347e-08
alternative hypothesis: true location shift is not equal to 0
```

TEST 3

In this test, I want to see if the opinions of the participants who work in a rated company about effect of CRAs on countries. Figure *c.1* provides the descriptive statistics. The summary shows that the data has around 1.37 standard deviation with 4 median and 3.17 mean. Moreover, in *Figure c.2,* the histograms show the distributions of two variables which are observed that they are not normal, and SW approved these by rejecting null hypothesis of data are normally distributed.

Figure c.1

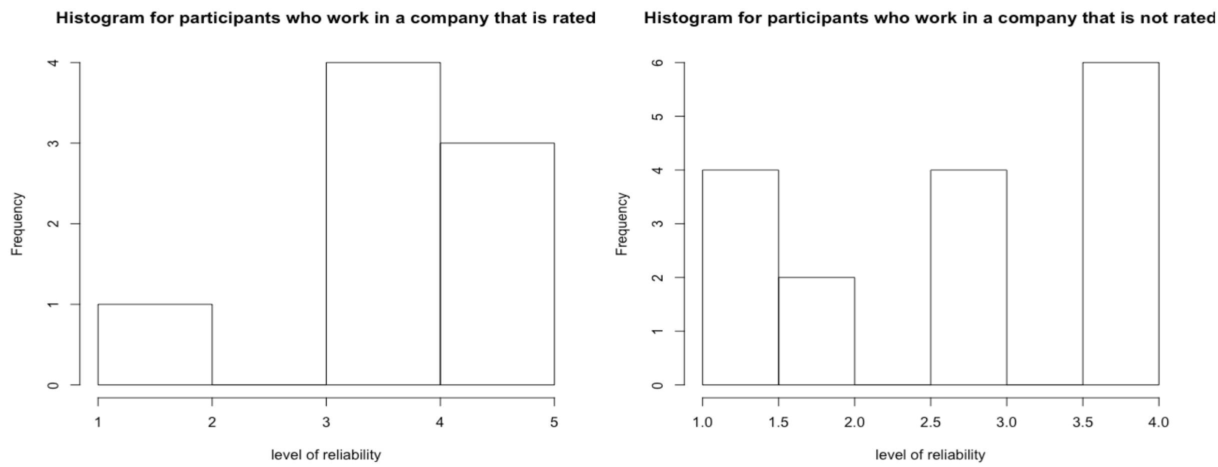
	RATED	NOT RATED	Total
std	1,309	1,238	1,373
median	4	3	4
mean	4,000	2,750	3,167
Number of Observant	8	16	24

For this hypothesis, MW test is applied with the null and alternative hypothesis:

H0: Opinion about effect of CRA on country is not related to participant's who works in a company rated

H3: Opinion about effect of CRA on country is related to participant's who works in a company rated

Figure c.2




```
Shapiro-Wilk normality test

data:  H3$RATED
W = 0.59795, p-value = 5.861e-07
```

As a result of the test, it can be seen in *Figure c.3,* p-value shows that the difference between two variables is statistically significant since p-value is lower than 0.05. Therefore, null hypothesis of "Opinion about effect of CRA on country is not related to participant's who works in a company rated" can be rejected.

Figure c.3

```
Wilcoxon rank sum test with continuity correction

data:  H3$RATED and H3$CRAEFFECTCOUNTRY
W = 116, p-value = 0.0002234
alternative hypothesis: true location shift is not equal to 0
```

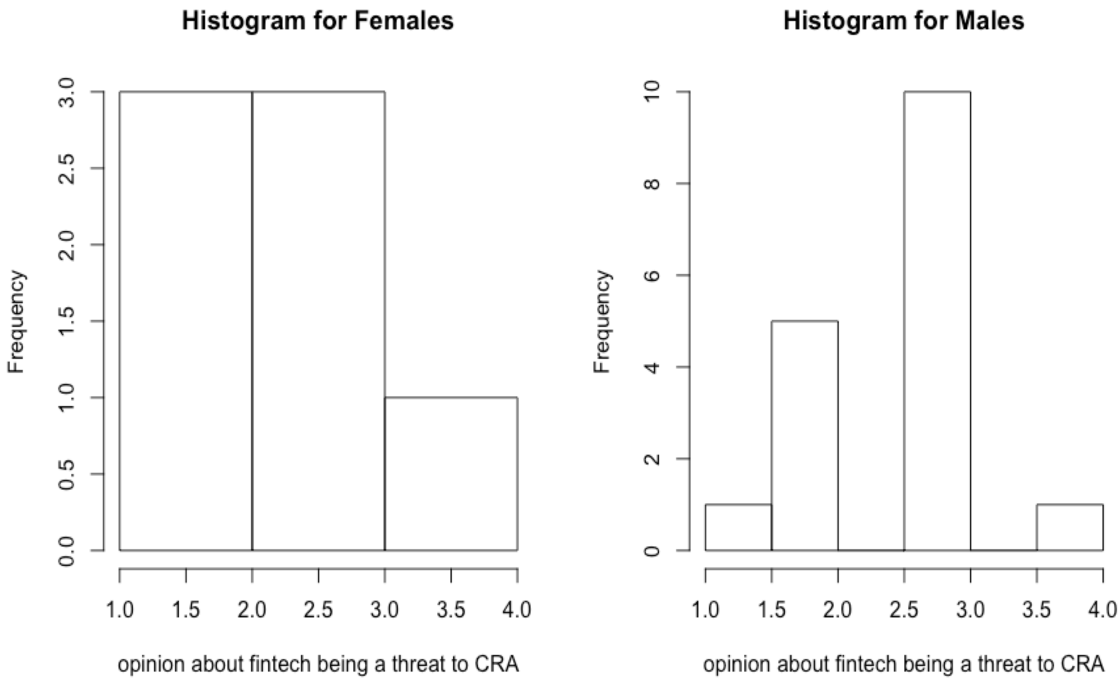
TEST 4

Participants were asked if Fintech companies pose a series threat to CRAs. *Figure d.1* provides the descriptive statistics. The summary shows that the data has around 0.77 standard deviation with 3 median and 2.62 mean. Moreover, the histogram shows that the distribution between female and male are not normally distributed, also SW approved that by rejecting null hypothesis of data are normally distributed which are shown in *Figure d.2*.

Figure d.1

	FEMALE	MALE	Total
std	0,976	0,702	0,770
median	3	3	3
mean	2,571	2,647	2,625
Number of Observant	7	17	24

Figure d.2




```
        Shapiro-Wilk normality test

data:  H4$FINTECHTHREAT
W = 0.84009, p-value = 0.001439
```

For this hypothesis, MW test is applied with the null and alternative hypothesis:

H0: Opinion about Fintech being a threat to CRAs is not related to gender

H4: Opinion about Fintech being a threat to CRAs is related to gender

As a result of the test, it can be seen in *Figure d.3,* p-value shows that the difference between two variables is statistically significant since p-value is lower than 0.05. Therefore, null hypothesis of "Opinion about Fintech being a threat to CRAs is not related to gender" can be rejected.

Figure d.3

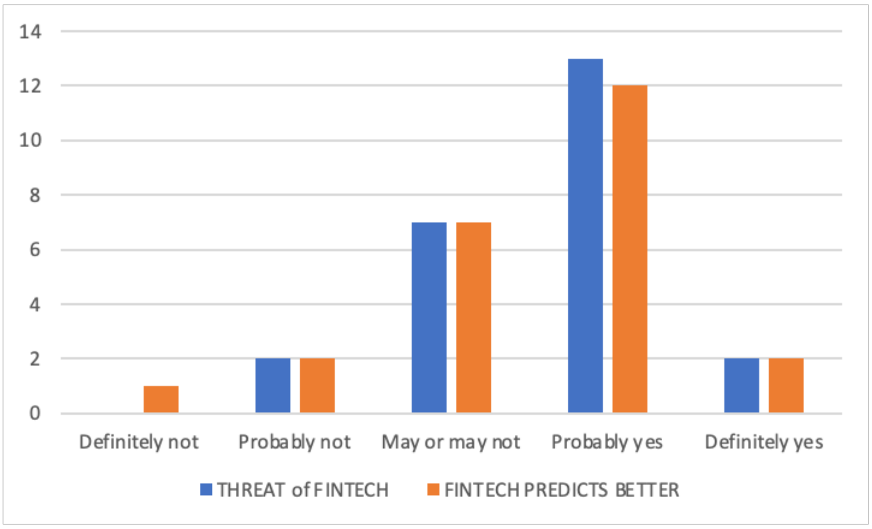
```
        Wilcoxon rank sum test with continuity correction

data:  H4$GENDER and H4$FINTECHTHREAT
W = 100.5, p-value = 2.85e-05
alternative hypothesis: true location shift is not equal to 0
```

TEST 5

In this test, I want to see if the answers about fintech being threat to CRA and fintech companies can predict the credit risk better than CRAs, are related. Figure *e.1* provides the descriptive statistics.

Figure e.1

	THREAT of FINTECH	FINTECH PREDICTS BETTER
std	0,770	0,933
median	3	4
mean	2,625	3,500
Number of Observant	24	24



For this hypothesis, chi-squared test is applied with the null and alternative hypothesis:

H0: Opinion about Fintech being a threat to CRAs is not correlated to the opinion that Fintech produces better prediction

H5: Opinion about Fintech being a threat to CRAs is correlated to the opinion that Fintech produces better prediction

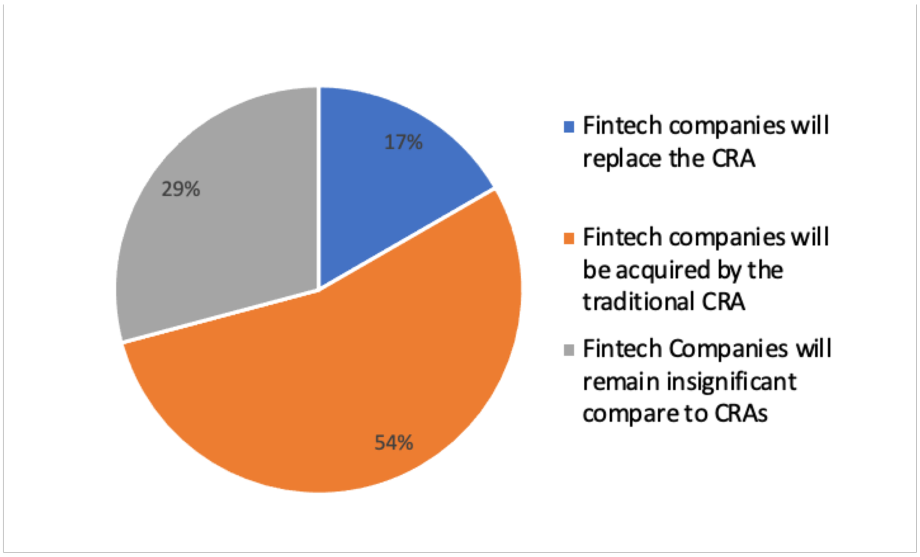
As a result of the test, it can be seen in *Figure e.2,* p-value shows that the difference between two variables is not statistically significant since p-value is higher than 0.05. Therefore, null hypothesis of "Opinion about Fintech being a threat to CRAs is not correlated to the opinion that Fintech produces better prediction" cannot be rejected.

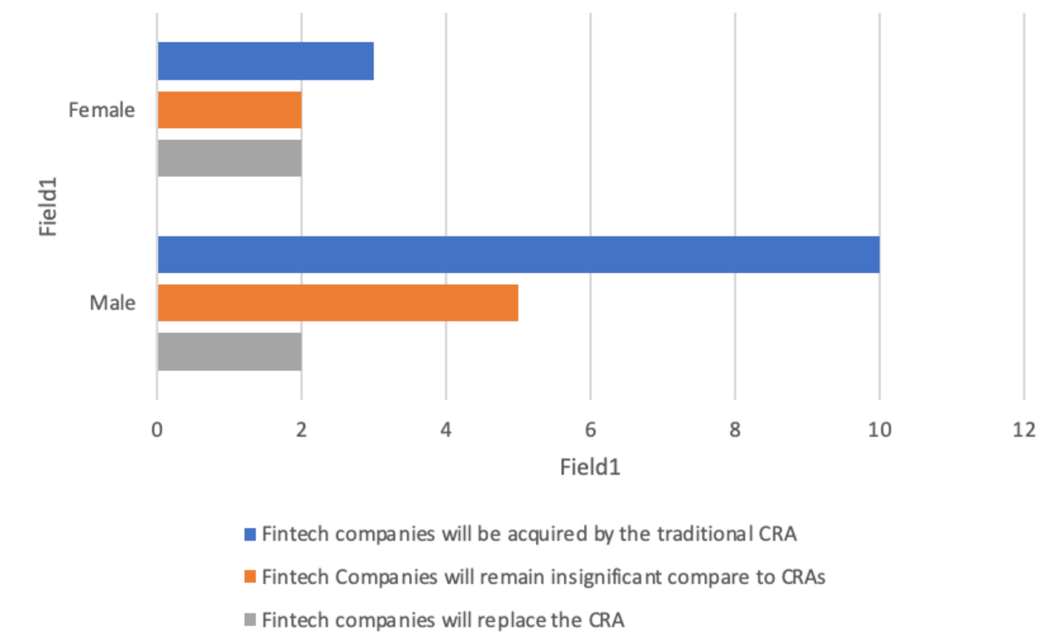
Figure e.2

```
                    Pearson's Chi-squared test

data:  H5$FINTECHTHREAT and H5$PERFORMFINTECH
X-squared = 20.1, df = 12, p-value = 0.06521
```

TEST 6

Figure f.1





Participants were asked to select one of the three options to the question of "How do you think that CRAs and Fintech companies might interact?". 54% of participants foresees that fintech companies will be acquired by CRAs, 29% of participants thinks that fintech companies remain insignificant compared to CRAs, while 17% of participants thinks that fintech companies will replace the CRAs. The summary result can be seen in *Figure f.1.*

In this test, I want to see if the answer to this question is related to the gender. For this hypothesis, chi-squared test is applied with the null and alternative hypothesis:

H0: The choice does not differentiate based on gender

H6: The choice differs based on gender

As a result of the test, it can be seen in *Figure f.2,* p-value shows that the difference between two variables is not statistically significant since p-value is higher than 0.05. Therefore, null hypothesis of "The choice does not differentiate based on gender" cannot be rejected.

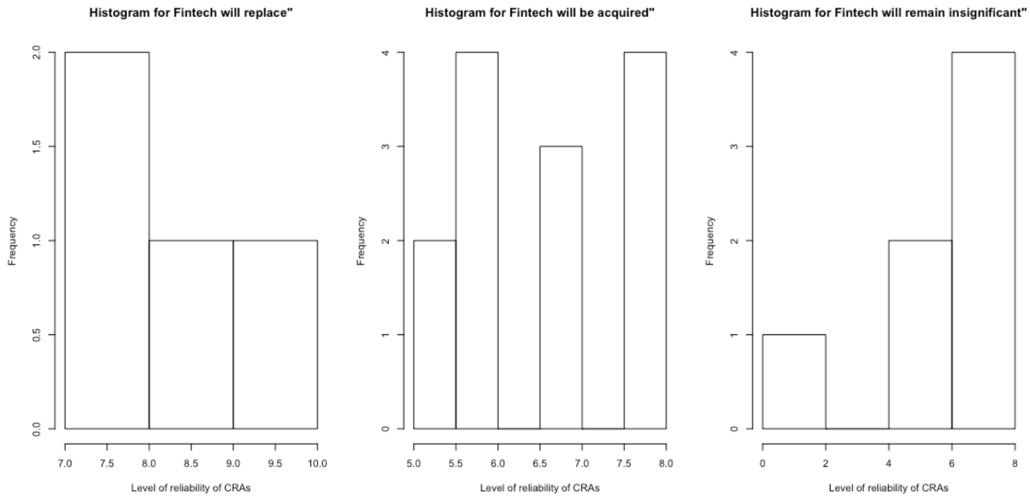
Figure f.2

```
        Pearson's Chi-squared test

data:  H6$THECHOICE and H6$GENDER
X-squared = 1.0749, df = 2, p-value = 0.5842
```

TEST 7 – TEST 8

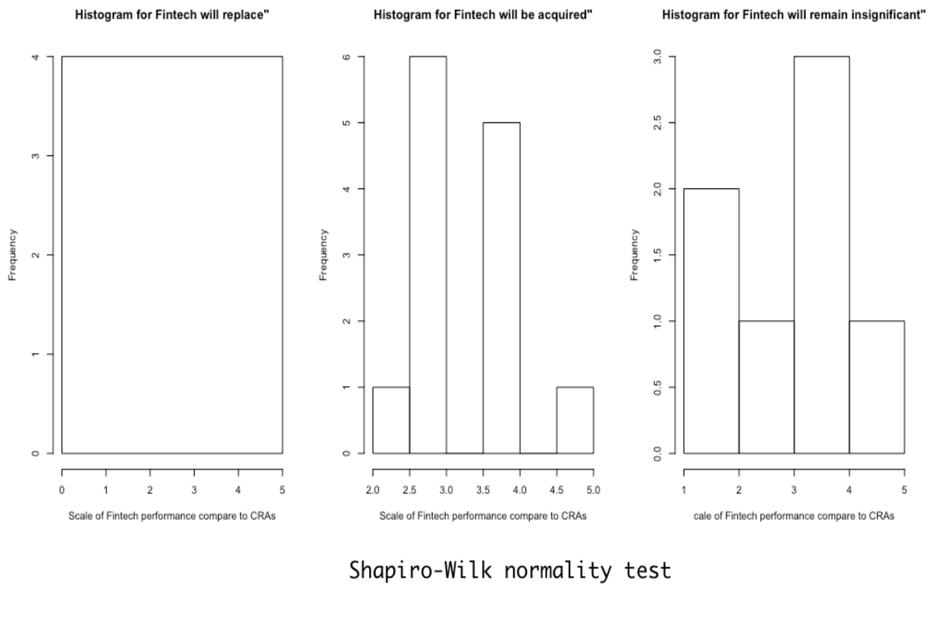
Participants were asked what they foresee about the future of CRA and Fintech companies, and how reliable they find CRAs and opinion about fintech perform better credit risk assessment compared to CRAs. I want to test if reliability level participants choice is related to the answers about the future of Fintech and CRAs and to their opinions for fintech's performance. *Figure g.1* and *Figure g.2* provide histograms and results of SW normality test respectively. Both histograms and SW tests confirm that they are not normally distributed.

Figure g.1




```
Shapiro-Wilk normality test

data:  H7$RELIABILITY
W = 0.84665, p-value = 0.001896
```

Figure g.2




```
Shapiro-Wilk normality test

data:  H8$PERFORMFINTECH
W = 0.85686, p-value = 0.002938
```

Two different hypotheses were built, and KW test is applied to each with the null and alternative hypothesis:

TEST 7

H0: The Level of Reliability of CRA is not related to the choice

H7: The Level of Reliability of CRA is related to the choice

Figure g.3: Result of TEST 7

```
	Kruskal-Wallis rank sum test

data:  H7$RELIABILITY by H7$THECHOICE
Kruskal-Wallis chi-squared = 5.3173, df = 2, p-value = 0.07004
```

TEST 8

H0: Opinion about Fintech performs better to CRAs is not related to the choice

H8: Opinion about Fintech performs better to CRAs is related to the choice

Figure g.4: Result of TEST 8

```
	Kruskal-Wallis rank sum test

data:  H8$PERFORMFINTECH by H8$THECHOICE
Kruskal-Wallis chi-squared = 1.8194, df = 2, p-value = 0.4027
```

As a result of the tests, it can be seen in *Figure g.3 and Figure g.4,* p-values for tests show that the differences between two variables are not statistically significant since p-values are higher than 0.05., Therefore, null hypotheses of “The Level of Reliability of CRA is not related to the choice” and “Opinion about Fintech performs better to CRAs is not related to the choice” cannot be rejected.

Summary: I built total eight hypotheses for the survey of professionals. The *Table 6* summarizes the hypotheses, which tests were used, results of the tests and meaning of the results.

Table 5

	HYPOTHESES for SURVEY of PROFESSIONALS	TEST	RESULT	MEANING
TEST 1	H0: The level of reliability of CRA is not related to degree level H1: The level of reliability of CRA is related to degree level	KW	Don't Reject Null	No Relationship
TEST 2	H0: The level of reliability of CRA is not related to gender H2: The level of reliability of CRA is related to gender	MW	Reject Null	Relationship Observed
TEST 3	H0: Opinion about effect of CRA on country is not related to participant's who works in a company rated H3: Opinion about effect of CRA on country is related to participant's who works in a company rated	MW	Reject Null	Relationship Observed
TEST 4	H0: Opinion about Fintech being a threat to CRAs is not related to gender H4: Opinion about Fintech being a threat to CRAs is related to gender	MW	Reject Null	Relationship Observed
TEST 5	H0: Opinion about Fintech being a threat to CRAs is not correlated to the opinion that Fintech produces better prediction H5: Opinion about Fintech being a threat to CRAs is correlated to the opinion that Fintech produces better prediction	Chi Squared	Don't Reject Null	No Relationship
TEST 6	H0: The choice does not differentiate based on gender H6: The choice differs based on gender	Chi Squared	Don't Reject Null	No Relationship
TEST 7	H0: The Level of Reliability of CRA is not related to the choice H7: The Level of Reliability of CRA is related to the choice	KW	Don't Reject Null	No Relationship
TEST 8	H0: Opinion about Fintech performs better to CRAs is not related to the choice H8: Opinion about Fintech performs better to CRAs is related to the choice	KW	Don't Reject Null	No Relationship

As a result of the test of the survey for professionals, I decided to conduct and interview to have a deeper understanding about the possible relationship between fintech and CRAs. In this survey, I could not find any relations, limited to this survey questions, related to the answers to question of possible interaction between fintech companies and CRAs. In the part 3.3.3, the interviews that I conducted will explained more in detail.

3.3.3 Interviews

An interview is defined as a purposeful discussion between two or more people helping to collect reliable data for relevant research (Saunders, Lewis, & Thornhill, 2009). There are three different types of interviews: fully structured, semi-structured and unstructured. Fully structured interviews are built with pre-determined questions with fixed wording, while semi-structured interviews are the interviews that has an interview guide that is used as a checklist (Robson & McCartan, 2016). Moreover, in semi-structured interviews, the questions and their orders can be changed, new questions can be added while existing one can be removed according to the flow of an interview. Lastly unstructured interviews that can be completely informal letting the conversation to develop within the area (Robson & McCartan, 2016). In this thesis, semi-structured interviews are conducted. The interviews of Dr. Berker, Mr. Pediroda and Mr. Zelyut are presented in *Appendix 3, Appendix 4* and *Appendix 5* respectively.

Purpose

The purpose of the interviews is to obtain a deep understanding of the respondent's world about the related topic. To able to do that, in this thesis I selected the interviewees carefully, so that I can represent every aspect of this thesis. Therefore, interviewees are representing the three side of this thesis' topic: a professional that represents traditional credit rating agencies, a professional that represents the fintech side of this thesis and a professional that represents the investor's point of view. I wanted to investigate how the answers will differentiate given the different backgrounds and experiences of the interviewees. In the interview questions, before asking directly about the future expectation of CRAs and fintech companies, I wanted to investigate reasons that can drive to the answer of the main (last) question. Therefore, first I wanted to understand what they think about the CRAs and Fintech companies in general. In order to understand this, I asked the questions to describe the importance of CRAs, what they think about fintech companies and what the biggest strength and weakness of CRAs. I continued the questions asking about the integration of fintech and financial institutions without including CRAs specifically to have general idea. I ended the interviews asking the main question of this thesis that is what future they foresee about fintech companies and CRAs. In this manner, these are the questions I asked during the interviews:

1. What do you think about the role of credit rating agencies in today's financial markets?

2. In your professional experience what are the biggest strength and the biggest drawback of CRAs?

3. What do you think about fintech companies in terms of accountability, professionality, and reliability?

4. Do you think that fintech companies pose a serious competitive threat to more traditional financial institutions? Why/Why not?

5. Have you ever heard of a fintech credit rating agency?

6. What do you think are the biggest changes that Fintech may bring about for CRAs?

7. What futures do you foresee for FinTech and CRAs?

Back up questions

- In case interviewer thinks Fintech is dangerous or unreliable - (do you think should the regulators do something to protect the financial institutions against FinTech companies and what can be done?)

- In case interviewer thinks fintech companies will remain insignificant compare to CRA: If I ask the same question for banks, would your answer be different

Next part will be divided into two. The first part will give a general background of the interviewees. In the second part, I will give a summary of the interviews by overviewing and comparing the answers. In the summary part, I also prepared a table, Table 7, which will provide a brief summary for the interviews.

The Backgrounds

Dr Ayse Botan Berker is the founding partner and chairperson in Merit Risk Management and Consultancy in Turkey since 2012. Between the years of 1999 and 2012, she worked at Fitch Rating Istanbul as a managing director.

Valentino Pediroda is the CEO and the founder of first fintech credit rating agency in Europe: ModeFinance.

Evren Demir Zelyut is the founder of Avrasya Investment Company in Turkey. He is also an economist and works as a journalist.

Summary

Every interviewee pointed out the importance of CRAs by stating that “very important”, “very valuable”, “very helpful”, especially for providing information to the financial market. Dr. Berker stated that the existence of a lot of information in the financial market so CRAs’ role is important and helpful in order to understand this information with the summary outcome of the ratings, she explained as these information “cannot be absorbed by an ordinary investor”. On the other hand, Mr. Pediroda explained the importance of CRAs saying that “everything is related to the spread, spread is related to the rating”. He also added that having an investment grade is important for big investors to be profitable.

From the interviews it emerged that, having an old history is one of the biggest strengths of the traditional CRAs. Furthermore, for the strengths of CRAs, Mr. Zelyut added having expert staffs while Mr. Pediroda added having a big name, being famous. Dr Berker also mentioned the high ability of making comparison between the entities due to having the largest sample of rating through the history. As a drawback points, Mr. Zelyut and Dr Botan stated the similar issues which is the information they provided may not completely reflect the situations that are evaluated. Mr. Zelyut thinks that it is due to CRAs' ability to evaluate the signals politically and socially is weak. On the other hand, according to the Dr Berker's opinion, because of the information bias in emerging market countries, global rating agencies may not be able to catch that bias. They explained that bias from local CRAs' and global CRAs' perspectives. She pointed out the dynamic differences between emerging and developed markets lead limited understandings in CRAs. In other word, for global CRAs, it is difficult to understand the bias in emerging market countries sighting from state agencies, and for local credit rating agencies, it is difficult to catch the dynamics of other parts of the world due to minimal understanding about rest of the world. She suggested that "We need something in between, a global rating agency which can operate more locally, they call those Glocal Agencies which does not exist". Mr. Pediroda on the other hand, sees the biggest weakness of traditional CRAs is lack of flexibility to adopt fast change in market.

Mr. Pediroda and Mr. Zelyut think that there is a competition in the market and the fintech companies pose a threat. When I asked the question about whether fintech companies pose a threat to traditional financial institutions to Mr. Pediroda, he said "absolutely yes", he added that "I see the banks, I see in a lending process". However, Mr. Pediroda stated that this competition and threat are depend on the market, so that not in every market fintech companies present a threat but he definitely thinks that in some markets they pose serious competitive. On the other hand, Dr Berker thinks that there is no war between the fintech and traditional financial institutions, the market is big enough to both and added that some level of competition is healthy, "market is very large; I think there is room for both to grow more".

All of the interviewees agree that fintech will provide many benefits to the traditional CRAs. Mr. Pediroda pointed out that the automatization and digitalization play and will play a great role in credit risk assessment. Dr Berker stated that fintech's ability to process the big data combining with CRA's several years' worth of accumulated data will create a unique position in terms of data provider. Mr. Zelyut talked about the higher speed in providing reports as a result of fintech's integration to CRAs, as well as reduced the costs of reports with quick spread to everyone.

Lastly, for the future of Fintech and CRAs, Mr. Zelyut thinks that once the fintech companies acquire necessary licenses, different scenarios will be observed in the market including the fintech CRAs will be able to compete with traditional CRAs. On the other hand, Mr. Pediroda and Dr Berker shared the similar opinions that Fintech CRAs will exist in their own markets rather than competing with traditional biggest CRAs. Mr Pediroda stated that "If you go against to the classical market, there is hope, but if you see new markets in the rating agency, rating market, of course in automatization and digitalization, there, we can play in our role in our market." He finished the interview saying, as a founder of first fintech CRA, "We are a player in the market that our own creation".

Table 6: Interview Summary

		Ayse Botan Berker	Valentino Pediroda	Evren Devrim Zelyut
INTERVIEW INFORMATION	**Position**	Managing Partner - Chairperson of Merit Risk Management	Founder and CEO of ModeFinance	Founder of Avrasya Investment
	Interview Language	English	English	Turkish
	Interview Duration	18 Minutes 30 seconds	11 Minutes 30 seconds	6 minutes 40 seconds
	Communication Type	Telephone Call	Google Meeting	Google Meeting
VERY BRIEF SUMMARY OF INTERVIEW	**Role of CRAS in Financial Market**	Very valuable in general - Very helpful as a information provider	Very important for big investors, very important having a investment grade from big CRAs	Good guidance in terms financial situation
	STRENGTH of CRAs	Their Position	Big and strong names	Expert Staff
	WEAKNESSES of CRAs	Objectivity	Lack of fast adoptation to the change in market - clients	Lack of evaluation socially and politically
	OPINION ABOUT FINTECH	High ability to process big data - but needs to be regulated	It depends on fintech by fintech	It depends on the company and references
	ARE FINTECH COMPANIES THREAT TO FINANCIAL INSTITUTIONS	Not a competition - enough room for both in the market	In some markets yes, especially in small markets	The roles will be shared with digitalization
	FUTURE OF CRAS AND FINTECH	They grow together	Some partnership, Fintech will be insignificant in classical market, very significant in new market	Different scenarios will be observed

In conclusion, it can be seen from the answers that they share the common thoughts but the reasons they used to support their common positions differ between the interviews. It can be observed that, Mr. Pediroda focuses on more digitalization and automatization of the ratings, while Mr. Zelyut more focuses on also digitalization, but he also adds the cost advantage, more reports that are more achievable from an investor perspective with the integration of fintech in CRAs. On the other hand, given the many years of experience, Dr Berker pointed out very important insights giving detailed explanation and examples about CRAs and how fintech and CRAs will integrate. Interviews provided explicit ideas and reasoning that cannot be attain from the surveys. Thanks to the interviews, I discovered a different angle that cannot be discovered from the surveys, which is the idea of Fintech CRAs existing in a different market or creating a new market. It can be said that interviewees given their positions, provided a new and different point of view about the position or possible positions of fintech in CRAs.

CONCLUSION

Today, CRAs have a crucial position in the global market. Its importance, rising popularity and being highly dominance with the big three names pose curiosity about their future positions. On the other side, with the ongoing and fast developments in technological innovations, FinTech became a hot topic in not in the financial market but in the world. The purpose of this thesis is to bring these two powerful topics together and explore the FinTech's effect on CRAs. At the end, it created the main research question as well as the title: Fintech in Credit Rating Agencies: Evolutionary or Revolutionary?

The thesis first provided theories of credit rating agencies and fintech to inform the reader about the backgrounds of the two main topics of this thesis: CRAs and Fintech. In this manner, the first chapter of this thesis gave a detailed information about the CRAs' history, their definition and evolution through the history. Furthermore, the biggest three CRAs were introduced, and their credit risk rating methodologies were explained. On the other hand, in the second chapter of this thesis, fintech's history, its description and dimensions were described. Second chapter also provided the technologies used in credit risk evaluation. Moreover, modeFinance company, a fintech CRA, was introduced together with explanation of its rating methodology. Other than informing the reader about the theory and presenting two different credit risk rating methodology in the first two chapter, a research was also done to explore this effect. In order to do that first, two surveys were conducted to non-professional people and professionals. One of the most important observation from the survey with non-professionals is that more than half of the participants do not know what a credit rating agency is. This thesis research question was asked to the people who knows the CRA, giving three possible options to choose one. 46% of the participants selected the option of "Fintech companies will be acquired by CRAs", 43% of participants selected the option of "Fintech companies will replace the CRAs" and 11% of participants selected the option of "Fintech companies will remain insignificant compared to CRAs". It is also observed that knowledge of what a CRA is related to the being employed or unemployed. Therefore, another survey is conducted to professionals. The research question was also asked to professionals giving the same options. 54% of the professional participants selected "Fintech companies will be acquired by CRAs", 29% of the professional participants selected "Fintech companies will remain insignificant compared to CRAs" and 17% of the professional participants selected "Fintech companies will replace the CRAs". As limited to survey questions, nothing was found related to the chooses to this question. At the end, an interview is conducted to three professionals. Dr. Botan Berker worked in a CRA as a managing director for over 12 years, so she is a good representative to acquire a perspective from someone experienced in a global CRA, Fitch. On the other hand, Mr. Valentino Pediroda is the founder of the only fintech CRA in Europe, Modefinance, being the perfect representative to have a perspective from experienced in Fintech sector. Lastly, Mr. Evren Zelyut who is the founder of an investment company, Avrasya Investment, and journalist and economist, so having a good representative outside the two opposite perspectives. As a conclusion, Mr. Pediroda and Dr. Berker shared the same opinion about the future of Fintech and CRAs: they will not be competing with traditional CRAs and be exist in their own market and grow together. On the other hand, Mr. Zelyut had stronger opinion compare to Dr. Berker and Mr. Pediroda, thinking that different scenarios will be observed which including fintech companies will lead the CRA market so that they will be in a competition.

The main purpose of the thesis was to provide the reader with a clear overview about CRAs and fintech. Moreover, from the theoretical part of this thesis, the readers can understand the differences between traditional CRAs and fintech CRAs, their improvements through the history and their rating processes. The purpose of this thesis as explained before is to explore if the fintech will be evolutionary or revolutionary in CRAs. Of course, it is not possible to conclude as it is evolutionary or revolutionary. Nevertheless, it can be said that maybe being evolutionary or revolutionary is not much different than each other. It can be observed from the interviews that CRAs and fintech need each other: CRAs reserve so much data in their hands and fintech companies have ability to manage this kind of data. Therefore, it can be seen as it is a natural evolution that can be partially revolutionary for both sides. Mixing these two is likely to be revolution because now a new tool, a new market will be available.

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Appendix

Appendix 1: Survey for non-professionals

Q1. Do you know what is a Credit Rating Agency (CRA)?

Q2. Which one of the following companies is a credit rating agency(CRA)?

Q3. Please choose one of the following option. Which one do you think is the best definition for a credit risk rating given by credit rating agencies?

Q4. In your idea, which one of the following options is the most important result of credit ratings assigned by credit rating agencies?

Q5. What is your country's credit rating category?

Q6. How important is a credit rating agency(CRA)?

Q7. Do you think credit rating can affect the economy of a country?

Q8. Do you think credit rating agencies have an influence on individuals?

Q9. How reliable are credit rating agencies? Please rate of scale of 0-10 with 0 being not at all reliable and 10 being extremely reliable.

Q10. Which financial technology (FinTech)'s services do you use the most?

Q11. Does technology play an important part in our life?

Q12. Will FinTech play a big part in our future?

Q13. Please rearrange the order of the following FinTech products placing them in decreasing order from the most to the least famous in your view

Q14. Do you think one day cryptocurrency could replace cash?

Q15. On a scale from 0-10, how much do you trust technology?

Q16. On a scale from 0-10, how safe do think to use FinTech services? For example, when you are making online money transfer or online payment, how comfortable do you feel yourself for these transactions?

Q17. I prefer traditional banks (Physical Bank) over internet-only banks

Q18. To transfer money I prefer to go to a bank rather than doing online

Q19. For my payments (such as bills), I prefer to pay my bills in person rather than online

Q20. I prefer carrying physical cards rather than using digital wallets

Q21. Imagine that you are considering lending money to someone. Which of the following options would you use to determine this person's ability to repay your money timely and completely?

Q22. Which of the following options represents the reason for your answer to the previous question?

I prefer human interaction

I find technology unreliable

All of the above

Q23. Which of the following options represents the reason for your answer to the previous question?

I find technology faster or easy to use

I find technology more reliable than human Human's opinion can be manipulated or biased

All of the above

Q24. Imagining that financial technologies (FinTech) may play a role in creditworthiness assessment, how do you think that credit rating agencies and FinTech companies might interact? Which of the following scenarios do you think is more likely to occur?

Q25. What is your gender?

Q26. How old are you?

Q27. What is the highest level of school you have completed or the highest degree you have received?

Q28. Are you currently working?

Q29. Where are you from?

Appendix 2: Survey for professionals

Q1. What is the Primary use of Fintech in your workplace?

Q2. How your company is developing Fintech?

Q3. How strong an effect do you think FinTech will have on your company?

Q4. How important FinTech adoption for your company?

Q5. What type of effect do you think FinTech's adoption will have on your job?

Q6. Is your company rated by any credit rating agency(CRA)?

Q7. Is the company you work affected by your sovereign ratings?

Q8. Do you think credit ratings can affect the economy of a country?

Q9. Do you think credit rating agencies have an influence on individuals?

Q10. How reliable do you think credit rating agencies (CRAs) are? Please rate of scale of 0-10 with 0 being not at all reliable and 10 being extremely reliable.

Q11. Do you think that fintech companies pose a serious competitive threat to more traditional financial institutions?

Q12. Have you ever heard of a fintech credit rating agency?

Q13. Do you think can FinTech make better and more accurate credit risk assessment compare to credit rating agency's assessments?

Q14. How do you think that credit rating agencies (CRAs) and FinTech companies might interact? Which of the following scenarios do you think is more likely to occur?

Q15. Can you tell me briefly the reason for your answer to the previous question?

Q16. What is your gender?

Q17. How old are you?

Q18. What is the highest level of school you have completed or the highest degree you have received?

Q19. What is your job title?

Q20. Are you currently working?

Q21. How many employees work in your establishment?

Q22. Where are you from?

Appendix 3: Ayse Botan Berker Interview

1. *What do you think about the role of credit rating agencies in today's financial markets?*

I find them very valuable because there are a lot of information in the financial markets which cannot be absorbed by an ordinary investor so the summary outcome of a rating will be very helpful in their investment decisions rather than trying to understand all the available information and absorb all those.

2. *In your professional experience, what are the biggest strength and the biggest drawback of CRAs?*

That is a cliche actually, my stress on their objectivity because, objectivity in the sense that it is very difficult to understand that Dynamics of each country and each market. The ratings for developed markets where the information asymmetry is minimal when you compared to the underdeveloped market which are emerging markets. So, the availability of the information and existed of established rules of law in those countries make rating agencies business more feasible and effective. But in emerging market countries, it doesn't matter if the rating is for the government rating or the sovereign rating or any entity in that country, there is information bias in those countries sighting from state agencies. So, to understand that bias is difficult for a global rating agency. But on the other hand, if we concentrate on local rating agencies, they might be more biased towards their own country entities in terms of ratings. So their rating of the rest of the world is less, I just want to stress on both sides, you know, from local country perspective, a local rating agency has a minimal understanding of the rest of the world so when they compare their own entities to their sectoral peers, in the other parts of the World, than I would not rely on that information a lot and from a global rating agency perspective it is the other way around. Their understanding of the local markets is limited I would say, I mean the dynamics of those market system is limited for global rating agencies so I think we need something in between a global rating agency which can operate more locally they call those glocal agencies, which doesn't exist. Fitch tried to do that. But to adopt the regulation of all countries is difficult when they are operating. They have tried to operate in different countries with staff from the local staff doing that business. But still that was not the ideal case because they had to comply with global rules which are ESMA rules, the rating agency supervisor, and also they have to comply with local regulations and sometimes, rarely, but that can happen, the both of those regulations may not be parallel to each other. So, complying one of them may not the fit the other one. We cannot have ideal case, but I just want to point out something. After global crises of 2008 when it was a very common notion that rating agencies had failed, and people should not be relying on rating agencies. There was no other alternative to replace ratings. So after more than 10 years still rating agencies are there and we can say they are in a stronger position. Moreover, big CRAs' ratings based on relativities. They are not cardinal; they are ordinal which means you have to benchmark one entity to others in the sector or in similar features. When you think about the global rating agencies three of them, they have the largest sample of ratings so their ability to make a comparison is much higher than anyone else in the market.

3. *What do you think about fintech companies in terms of accountability, professionality, and reliability?*

Technological development and as with all other sectors, in financial sector making use of technology is feasible and it should be used more to understand past in order to make a projection for the future, a better understanding of past is important. Fintech companies like with their tools provided to artificial intelligence and all those can provide better understanding of processing very large amounts of data. So I think it is very important in that sense. But there should be rules and I believe all those regulators are looking the ways of prevention of cyber security and also for fintech companies, I believe, there will be more rules at here for.

4. *Do you think that fintech companies pose a serious competitive threat to more traditional financial institutions?*

Market is very large; I think there is room for both to grow more. So it is depend on, I don't think that is a competition, there is a competition, a limited competition, and a degree of competition is healthy. But I don't see that fintech companies will overrule and other conventional financial instructions will disappear, no, that won't happen. Financial instructions are intermediate institutions, when you are investing your money, many people want to have a feeling of human touch, they want to talk to someone, even though many of things can be handled through internet when on a simple file case. Still you can see many people who want a personal contact so I think that will continue. I mean, the importance or scale of fintech companies will expand but the others will stay there. They might use more fintech in their own companies. I don’t think that it is a war. That one of them will win. They will survive together. This is what I see the future as.

5. *Have you ever heard of a fintech credit rating agency?*

Recently yes. Actually, the company I worked for, it has its own models, rating models, which can be considered as fintech, because they are web-based models. They are only based on objective criteria, and you can just click on the web and ask for rating and you get it, it is different than from a traditional rating, where there are more subjective factors involved and you go and visit the company and whatever. And I think it will work. Actually, may not be replacing the requirement for bond issues. But for quicker decision making, fast decision making, that kind of ratings, fintech company ratings, will be improving and will be use more going forward. Even for a back, they can do their own analysis but also as a validation tool, they can use this to validate their own decision. Because it is a very objective tool. What do you think are the biggest changes that Fintech may bring about for CRAs?

6. *What do you think are the biggest changes that Fintech may bring about for CRAs?*

I think it is a difficult question, the thing is currently the global credit rating agencies are not only credit rating agencies, but they have also accumulated all the data for a hundred year that they have been operating, So they have substantial credit data in their hands. So, using that data through fintech tools will be importance advantages for them. And they are already providing some data to the market on corporates or any other required issue. So, I think that will enhance their dominance, not to on rating perspective, but on data provider perspective. They have a very unique position there.

7. *What futures do you foresee for FinTech and CRAs?*

I don’t think that they can go hand in hand, fintech CRAs can grow own their own and the others will stay there, as they are and improve their solid base through proving more data to the market. But other than that, there will be really more need for quick decision making and to validate your own decision making which will all help Fintech CRAs to grow more and more. Therefore, they can both grow in the same market. When you consider the recent changes regarding IFRS 9 which requires expected loss provisioning rather than loss provisioning for a default or for an existing loss, existing event. Now all corporates, all financial instructions, everybody in business have to make an assessment on expected loss and expected loss means creditworthiness, credit rating, default probability. And that cannot be provided by only existing global CRAs, not the global, but all the CRAs. So there has to be quicker, quick decision making through fintech CRAs. I see a good opportunity for both of them to grow.

Appendix 4: Valentino Pediroda Interview

1. *What do you think about the role of credit rating agencies in today's financial markets?*

I think very important especially for the big investors because at the end everything is related to the spread, and spread is related to the rating so at the end especially for the big investors, is quite important. We are also a credit rating agency so when we worked with asset managements, especially the classical asset managements, they follow the official credit rating but nothing aside. Because between to be a profitable and to be in investment grade is still very important. Especially if you are conservative and classical asset management

2. *In your professional experience, what are the biggest strength and the biggest drawback of CRAs?*

The strength is sure the name of the credit rating agencies with their history. Because for S&P, Fitch and Moody's, they have so much old story with the big names, and this is really the strength for them. The weak point is flexibility because they cannot adopt so fast to the change of the market and to the change of the needs of the clients.

3. *What do you think about fintech companies in terms of accountability, professionality, and reliability?*

For professionality, I can say that they are professional because of the high number of professional people. They are the people who are clever, professional coming from classical corporates and want to change their life, want to do something different. Therefore, they built the fintech companies make them official and professional.

For reliability it depends. Because being a small name in the finance world for young corporations is very hard because in financial word the name is quite important so for reliability. Because the history of the corporates is very important and normally fintech companies don't have so much history. Accountability is also depends on if they are small fintech or big fintech. So, it really depends on fintech by fintech – company by company.

4. *Do you think that fintech companies pose a serious competitive threat to more traditional financial institutions?*

Absolutely yes. I see the banks, I see in a lending process, I see that lending in SMEs. Of course, may be in some not very core market, small markets, but absolutely it can be very important competitor. But also depends, because sometimes they can have a partnership, sometimes just be a competitor but absolutely the role in some markets absolutely they pose serious competitive against the classical corporates.

5. *What do you think are the biggest changes that Fintech may bring about for CRAs?*

Of course, while I am answering this question I will talk about my company, because there are not any other fintech rating agencies, so I will say what did. We know and we are very aware that go against to CRAs like SP, Moody's is quite impossible. For example, I don't see that company like Volkswagen asking the rating from Modefinance against S&P, it is not the case. However, there is a huge market for the automatization and digitalisation for the credit risk assessments. So, at the end mainly asset management, all financial world need a risk assessment and to integrate the technology on a rating agency as an automatic platform is very interesting market. So what we are playing is a digital rating agency, an automatic rating agency. So this is where we can work against the big credit rating agencies. So if you go against to the classical market, there is no hope, but if you see new markets in the rating agency, rating market, of course in automatization and digitalisation, there, we can play in our role in our market. The conclusion is that there no hope to go directly against to classical CRAs but there is a space to do something in which they are not still doing. Therefore, it is something like we are a player in the market that our own creation rather than playing in an existing market dominated by traditional CRAs.

6. *What futures do you foresee for FinTech and CRAs?*

My opinion is that there can be some partnership between fintech CRAs and traditional CRAs. Moreover, Fintech CRAs will remain insignificant in the classical market, but I think they will be very significant in the new market

Appendix 5: Evren Devrim Zelyut

1. *What do you think about the role of credit rating agencies in today's financial markets?*

Now we know that the credit rating agency provides guidance to foreign investors regarding the financial situation of both companies and governments. I think the major rating agencies have played this role well so far.

2. *In your professional experience, what are the biggest strength and the biggest drawback of CRAs?*

One of the most important things as their strength is that they have an expert staff. And these experts analyse macroeconomic data well and naturally provide good guidance to investors about both companies and countries. Their weak sides are: When it comes to evaluating a country, it is not enough to just look at the macroeconomic data of that country. At the same time, we see that the signals coming from the political and social field are also effective on the behaviour of both consumers and producers. The biggest shortcoming of these credit rating agencies that I have seen over the years: they cannot read the political and social signals well. Therefore, reaching a conclusion only from the rate of change of growth, inflation, national income, or other figures can often cause difficulties in their estimations. This is their weaknesses as well.

3. *What do you think about fintech companies in terms of accountability, professionality, and reliability?*

Here is what comes to mind: When we come across a Fintech company, who are the references here? Are there users in our neighbourhood? Are there any complaints about it? Attention is paid to these, websites are examined. We look at the products they create and review them. Therefore, I think it would be more accurate to make an evaluation on the basis of companies by looking at such criteria. So, in general, Fintech companies are not like this, I think they should be evaluated on the basis of the criteria I just mentioned.

4. *Do you think that fintech companies pose a serious competitive threat to more traditional financial institutions?*

With Fintech, for example, or with digitalization, I believe that the role of CRAs will be shared with different companies or different actors will come into play. Of course, the more digitalization becomes, the more different players come into play in the economy and financial markets. In this context, they will continue the mission they have brought to this day, but they will not be alone anymore. We will now see Fintech companies next to them. I think they will be integrated into these markets in some way.

5. *Have you ever heard of a fintech credit rating agency?*

I heard that there are Fintech CRAs abroad, both Chinese and Indian.

6. *What do you think are the biggest changes that Fintech may bring about for CRAs?*

Once they bring speed, they will be able to produce faster reports. Secondly, the prevalence will increase with digitalization, that is, the reports produced will reach and spread quickly to everyone. Thirdly, these reports will somehow reduce their costs and have a cost advantage. Another point is the data and sample numbers in the reports: here, as the objectivity of the data is based on a more digital and technological basis, the objectivity will increase and the number of examples will increase as well. I think that more accurate comments and reports will be produced by using the larger data set provided by digitality rather than acting with a specific and limited data set.

7. *What futures do you foresee for FinTech and CRAs?*

As you know, Fintech companies work very closely with the banking system, so perhaps one of their biggest customers is the banking system. Capital markets and brokerage firms are among them. So here I think we will observe things like a Fintech company leading the market or being bought by traditional institutions and the Fintech company may be insignificant. How? We will see that once the Fintech company obtains the necessary licenses, it will also take part in the rating business. Or we will see existing credit rating agencies buy Fintech companies. In this way, there will be mutual cooperation from both markets. But I believe that Fintech companies will really bring a dynamism to this market and also make it widespread. In other words, credit rating agencies will not stay with big companies such as Moody’s, Standard Poor’s, Fitch and so on. We're going to see fintech companies compete as well, and I think that's going to be great. Why is that? Because with the competition, investors will see this in the world and prefer them who does not make more objective evaluations. There is such a situation.