# UNIVERSITA' DEGLI STUDI DI PADOVA

**DIPARTIMENTO DI SCIENZE ECONOMICHE ED AZIENDALI "M.FANNO"**

**CORSO DI LAUREA MAGISTRALE IN**

**ECONOMICS AND FINANCE**

# Unsecured Past Due Credit Evaluation: a Pricing Model

**RELATORE:**

**CH.MO PROF. BRUNO MARIA PARIGI**

Bruno Parigi

**LAUREANDO/A: JOAO MANOEL DOS SANTOS**

**MATRICOLA N. 1155360**

**ANNO ACCADEMICO 2018 – 2019**

Il candidato dichiara che il presente lavoro è originale e non è già stato sottoposto, in tutto o in parte, per il conseguimento di un titolo accademico in altre Università italiane o straniere.

Il candidato dichiara altresì che tutti i materiali utilizzati durante la preparazione dell'elaborato sono stati indicati nel testo e nella sezione "Riferimenti bibliografici" e che le eventuali citazioni testuali sono individuabili attraverso l'esplicito richiamo alla pubblicazione originale.

*The candidate declares that the present work is original and has not already been submitted, totally or in part, for the purposes of attaining an academic degree in other Italian or foreign universities. The candidate also declares that all the materials used during the preparation of the thesis have been explicitly indicated in the text and in the section "Bibliographical references" and that any textual citations can be identified through an explicit reference to the original publication.*

Firma dello studente

_______________________

# Index

# 1. Introduction

The aim of this dissertation is to offer to SME companies a quantitative model to price a basket of past due positions at the moment of their acquisition. In particular, the model that we will present is developed based on a sample made of past due unsecured loans issued to retail clients. The obstacle in evaluating this kind of asset is the absence of historical data about the debtor's financial condition and its previous commitment to the obligation, i.e. the asymmetric information between the seller and the buyer. In fact, the available information is often limited to general details about the debtor and the position. To overcome this problem, additional macroeconomic information can be added to the sample, in order to have a better performance of the estimate.

More than 10 years after the global financial crisis, some European countries have not reached the economic level in terms of GDP of the pre-crisis period.

One of the consequences of the crisis that started in 2008 was to create a stock of non-performing loans and other forms of past due credit, that resulted in a burden for corporate and financial entities. The presence of past due securities on banks' and companies' balance sheets had the double effect of restricting the issuance of credit from financial entities and to reduce the possibility of starting new investments for firms. This partially explains the increasing importance of alternative forms of financing, such as factoring activities, private lending or crowdlending.

The crisis hit Italy powerfully, leaving long lasting consequences. One of the consequences is the difficulty for companies to receive credit from banks and other lending entities, as highlighted by previous research. As reported by Cucinelli, that studied the correlation between lending activity and amount of NPL of Italian banks, "commercial banks reduce their lending activity in front of an increase in credit risk" (Cucinelli, 2015). The same result was obtained by Panetta in 2013 (Panetta, 2013).

European authorities and the national governments have tried different solutions to ease the issuance of financing solution for corporates and families, with the final goal of supporting and boosting the economy, obtaining indeed limited results. The main example is the monetary policy adopted by the ECB, that has shown to have a limited effect on the real economy. In fact, especially in Italy, inflation has been constantly under the target of 2%, while the amount of credits issued to SME has not varied accordingly to the monetary policy, as reported by Andrea Franceschini (Franceschini, 2019)

Since this is due to the high concentration of risky assets in the balance sheet of financial entities, a partial solution to the problem was found in the last few years. In fact, since the peak of the crisis of sovereigns, companies and financial entities have gradually reduced their exposures to past due credits, increasing the turnover amount of credits in the economic system (Franceschini, 2019).

A consequence of the reduction of non-performing credits on firms' balance sheet, is an increasing volume of securities that entered the secondary market of past due credits. As highlighted by Morya Longo, this secondary market increased in size at the point that there are few services, i.e. credit recovery agencies, compared to the quantity of assigned dossiers (Morya Longo, il Sole 24 Ore, 2019). The problem for SMEs operating in this sector is that they often do not have appropriate quantitative tools or professionals dedicated to evaluating the price of a basket of past due credits.

Notice that model that will be presented does not want to be exhaustive when evaluating the price of securities. In order to allow for adjustment, the model offers flexibility when inserting those inputs that tend to be company-specific. The advantage of this model is that it allows to evaluate one of the less accessible classes of past due positions, the one made of credits issued to individuals and families that are unsecured. The model returns the estimate of the final expected price through the discount cash flow methodology.

To achieve this goal, the dissertation first analyses the market for past due positions. Both the buy-side and the sell-side are considered. To have a clear estimate of the costs and to check the performance of the model, the thesis considers the national average metrics linked to credit recovery agencies. It then investigates more deeply the recovery process, isolating the more important cost items and other aspects of creditor and debtors linked to the underlying obligations.

We focus then on the datasets at disposal, by offering a descriptive analysis of the variables presented in the sample. The dataset contains information about more than 5,000 securities. Another supporting dataset describes all the movements (meaning the payments stream) regarding the 5,000+ positions collected on 12,192 records. All datasets are offered by Teseo srl, a credit recovery agency.

After offering the descriptive analysis of the sample, the thesis inspects how the different variables impact on the recovery rate. The recovery rate is calculated by dividing the recovered amount by total to recover and expresses the portion of the nominal amount that has been recovered. The impact of the variables on the amount recovered is obtained through an OLS regression.

To be able to model a discounted cash flow evaluation, the probability of recovery is estimated through a logistic regression. Also, the costs connected to the recovery process and the timing of the recovery is estimated from the movements dataset, allowing to calculate how much it takes to obtain a first payment, and how is the following stream of cash flows distributed.

Once all the inputs are obtained, net cash flows can be discounted and the present value calculated. Finally, by multiplying the present value for the probability of recovery, we obtain the expected present value of the basket of securities.

Hence, the operator has an estimate of the fair price of the securitization. As shown in the results of the model, the main variables that allow to estimate the price of a basket of past due credits are some general information about the debtor, such as the age, the residency and gender, together with specific aspects of the credits and additional macroeconomic data.

Moreover, the model offers to the user flexibility, allowing the operator to introduce company-specific variables for the estimate, and allows for further development, being used as a framework to develop non-linear with as machine learning and other non-linear techniques. However, it is a useful tool, especially for small and medium companies with little access to data and with no division inside the organization dedicated to the evaluation of past due positions.

## 2. The Italian Credit Market for NPLs

It is important to understand the NPL composition since financial institutions are the main source of credits entrusted to recovery agencies.

A definition for non-performing loan is not unique and differs among countries. According to the International Monetary Fund, there is however convergence on a common definition, considering an NPL as a loan of which "payments of interest and principal are past due 90 days or more […], or payments are less than 90 days overdue, but there are other good reasons to doubt that payments will be made in full" (A. Bloem and R. Freeman, 2005).

The lack of a global common definition and classification method of NPLs is indeed an issue. For the creation of a better regulatory and supervisory environment, the European financial authorities set a common definition and a shared treatment strategy for all euro area countries regarding NPE.

### a. NPL: Classification & Treatment

The classification of non-performing loans is given by the European Banking Authority (EBA, 2014). In October 2013, the EBA provided a common framework to all European financial institutions on NPEs classification and treatment. Before this date, financial institutions relied either on country-specific or on international definitions (such as the IRFS's one) of NPE, leading to a challenging environment for cross-border financial institutions as well as for the regulator.

The creation of a shared framework became necessary after the explosion of the financial and the sovereign crisis. This common set of criteria allowed to compare the asset quality of European financial institutions, operating as a starting point for the European banking union and its single supervision and resolution mechanisms for all euro-area financial institutions.

In EBA's final draft of July 2014, financial exposures have been confined in specific categories defined as:

- **Fully performing loans**: loans and debt securities that are not past-due and without risk of non-repayment and performing off-balance sheet items.

- **Assets past due below 90 days**: loans and debt securities up to 90 days past due. It comprehends also **unlikely to pay (UTP)** exposures, even if the identification in this category is based less on quantitative criteria and more on qualitative criteria fixed by the institution itself.
- **Forbearance**: forborne loans and debt securities (and eligible off-balance sheet commitments). This category collects debt positions where the debtor had specific concessions due to demonstrable financial difficulties. The concessions can be such as refinancing or modifications of the terms of the contract, among others.
- **Non-performing exposures:** loans and debt securities past due more than 90 days or unlikely to be repaid in full without collateral realization.

Particular effort is put in defining the borders between different categories, since the recognition criteria is essential to spot the quantity and quality of the assets of financial institutions.

Another classification is given by Bank of Italy (Bank of Italy, Circolare n° 232, 30/07/2008 updated at 11/12/2018) which reports three main categories of NPE:

- **Bad loans**, that are exposures to debtors that are insolvent or in substantially similar circumstances.
- **Unlikely-to-pay exposures,** aside from those included among bad loans, are exposures where banks believe the debtors are unlikely to meet their contractual obligations in full unless action such as the enforcement of guarantees is taken.
- **Overdrawn or past-due exposures**, aside from those classified among bad loans and unlikely-to-pay exposures, are exposures that are past-due by more than 90.

While the first categorization is used for European supervisory reasons, the one proposed by Bank of Italy is used for statistical purposes in order to maintain continuity with time series data previous to the publishing of EBA standards in 2013 (Bank of Italy, 2017).

Together with the EBA definition of NPEs, the European Central Bank provided guidelines for the treatment of NPLs (ECB, 2017). As stated by the document "Guidance to banks on non-performing loans" (European Central Bank, March 2017), the set of rules "is addressed to credit institutions within the meaning of Article 4(1) of Regulation (EU) 575/2013 (CRR)" (European Central Bank, March 2017), but it is applicable to "all Significant Institutions (SIs) supervised directly under the Single Supervisory Mechanism (SSM)" (ECB, 2017), especially those with high levels of NPLs or of forbearance or foreclosed assets, as well as with low provision coverage or an elevated Texas ratio[1]. The definition of significant institutions is given by the ECB "Guide to banking supervision" (ECB, 2014). According to the ECB's guide, a significant financial institution is a financial institution that satisfies specific criteria regarding the total value of its assets (national or cross-border), if it is a recipient of direct assistance from the European Stability Mechanism or is a one of the most significant credit institutions established in a Member State.

Even if the guidance on non-performing loans is not binding, banks deviating from its guidelines should explain the deviations and may be subject to further supervisory measures.

In the same document, the ECB defines different strategies to apply to NPE portfolios. The main blocks for the development and implementation of an NPL strategy are (ECB, 2017):

1. assessing the operational environment, including internal NPL capabilities, external conditions impacting NPL workout and capital implications;
2. developing the NPL strategy, including targets in terms of development of operational capabilities (qualitative) and projected NPL reductions (quantitative) over the short, medium and long-term time horizons;
3. implementing the operational plan, including any necessary changes in the organizational structure of the bank;
4. fully embedding NPL strategy into the management processes of the bank, also by including a regular review and independent monitoring.

Point 1 highlights the necessity for financial institutions to fully understand the environment banks are operating, considering both internal and external variables. The financial institution should then examine parameters such as the "scale and drivers of the NPL issue […], outcomes of NPL actions taken in the past […] and operational capacities (processes, tools, data quality, IT/automation, staff/expertise, decision making, internal policies, and any other relevant area for the implementation of the strategy) for the different process of the steps involved" (ECB, 2017). On the other hand, together with a self-assessment, financial institutions need to consider external parameters such as macroeconomic conditions, market expectations towards NPL levels and

[1] The Texas ratio is defined as: Texas Ratio = (Non-Performing Loans + Real Estate Owned) / (Tangible Common Equity + Loan Loss Reserves).

coverage ratio, NPL investor demand for portfolio sales, NPL servicing industry, tax implications for NPL write-offs and the regulatory, legal and juridical framework, both national and European.

For what concerns point 2, the ECB highlights specific strategies that may be adopted. It marks the possibility to hold the non-performing assets by operating forbearance measures and borrower assessments or through the outsourcing of the recovery process. As an alternative to the hold strategy, financial institutions can operate active portfolio reductions through sales or writing-offs of NPL that are considered unrecoverable. Finally, depending on the presence of a collateral or any other form of guarantee, financial institutions can recur to legal actions or change the type of exposure through foreclosure, debt to equity swap, debt to asset swap, or collateral substitution (ECB, 2017).

The strategy must be clearly defined in terms of a goal for NPL reduction and the relative time-bound, in a fully assessed environment. According to the ECB, this should lead to a correct implementation of the strategy in the form of an operational plan that "should rely on suitable policies and procedures, clear ownership and suitable governance structures" (ECB, 2017). Also "some high NPL banks might need to incorporate wide-ranging change management measures in order to integrate the NPL workout framework as a key element in the corporate culture" (ECB, 2017). This means that NPL reduction strategies may require credit institutions to develop their organizational and corporate structure in order to create divisions specialized in the process of credit recovery.

### b. Types of Credits

An elementary point in the NPL management is to fully assess the credit risk connected to the issuance of a loan *a priori*, in order to invest on assets of a good quality and to reduce the transformation rate of performing assets to non-performing exposure. Together with the creditworthiness of the borrower, the risk connected to a credit depends also on the nature of the credit itself. It is useful to understand the types of credit by considering different variables for its classification.

The first variable to consider is time, i.e. when the credit is issued and when it will be repaid. Based on this parameter we can highlight four types of credits (Martin and Mammott, 2014):

- **Revolving credit**: the borrower disposes of a maximum aggregate amount of capital, available over a specific period; during this period the borrower is allowed to draw down, repay and re-draw loans on the available funds during the term of the note. At the end of each period in which the loan is available – usually one, three or six months – the borrower carries a balance and makes a payment.
- **Open Credit**: it differs from the revolving credit in that the borrower must fully repay the total balance at the end of every period, and it has no maximum amount. Examples of open loans include many business credit cards.
- **Service credit**: it comes from agreements with service provider. A service or product is given periodically and is paid after its reception. Examples of service credit include heat, electricity, water, phone and similar services.
- **Installment credit**: in exchange for a specific amount of money, the borrower agrees to repay the capital amount plus interests in regular installments of a fixed amount over a set period. Examples of installment credit include car loans, mortgages, student loans, and most payday and check cashing loans.

Inside each category we can find specific types of loans, such as credit cards, mortgages, student loans or utility bills. Even if some of these are not bank credit, they can still be treated as credit securities, and are subjected to a recovery process similar to other types of unpaid bank borrowings.

Another important element to consider with regards to a credit security is to identify the nature of the borrower. We can distinguish between credits issued to companies and small or medium enterprises (SME), to family businesses, to retail, to the public administration and to financial institutions. Some types of debtors carry intrinsic higher risk due to the absence of public information or to no updating of the previously available one, leading to information asymmetry between the lender and its counterparty.

When evaluating credit securities, it is also important to consider the presence of a collateral. The collateral is defined as "as an asset that upon liquidation is adequate to cover most or all of the lender's risk exposure including principal, accrued interest and collection costs" (Nagarajan & Meyer, 1995). A collateral has a double function in reducing the risk of a loan. On one hand it operates as a signaling device: a borrower with a lower probability of default will be more inclined to accept a higher value of the collateral to lower the interest rate applied to a loan than borrowers with a higher probability of default. But collateral acts also as an enforcement device, securing loans against “both exogenous and endogenous risks that lead to loan default” (Nagarajan & Meyer, 1995). In both cases the main objective is to contrast effects deriving from asymmetric information, such as adverse selection and moral hazard. A loan secured by a collateral is called secured loan, as opposed to unsecured ones, which has no collateral as a guarantee.

Finally, the last relevant type of loan to take into account is the so-called consumer credit. Bank of Italy defines consumer credit as “a loan that can only be requested for personal needs, which are connected to private, family life” (Bank of Italy, 2018).

A consumer loan can be asked to directly purchase something, in which case it is called a special purpose loan and the lender usually pays the sum directly to the seller; alternatively, it can be requested because cash is needed, and it is then called non-specific loan. According to the Italian law, for a credit to be classified as consumer credit, the amount lent must lay between €200 and €75,000 and it cannot be for professional purposes (Bank of Italy, 2018).

Consumer credit can be in the form of revolving credit or installment credit. Installment credit is usually used for a specific purpose and the item purchased with it may serve as collateral for the credit issued, in case of default of the consumer. It has a lower interest rate if compared to revolving consumer credit, that is not used for specific purchases and hence lacks of collateral. Installment credit can also be in the form of personal loan without specific purposes. In this case other forms of guarantees can be asked, such as guarantee from third parties or the underwriting of an insurance policy, together with the possibility for the borrower to pay the installments directly with one fifth of their salary (Bank of Italy, 2018).

### c. NPL in Italy

The NPL market is a lively one in Italy. Since the peak of €341bn at the end of 2015, banks have increasingly reduced the amount of non-performing loans in their books, reaching €222bn in June 2018 as total gross book value (Pwc, 2018).

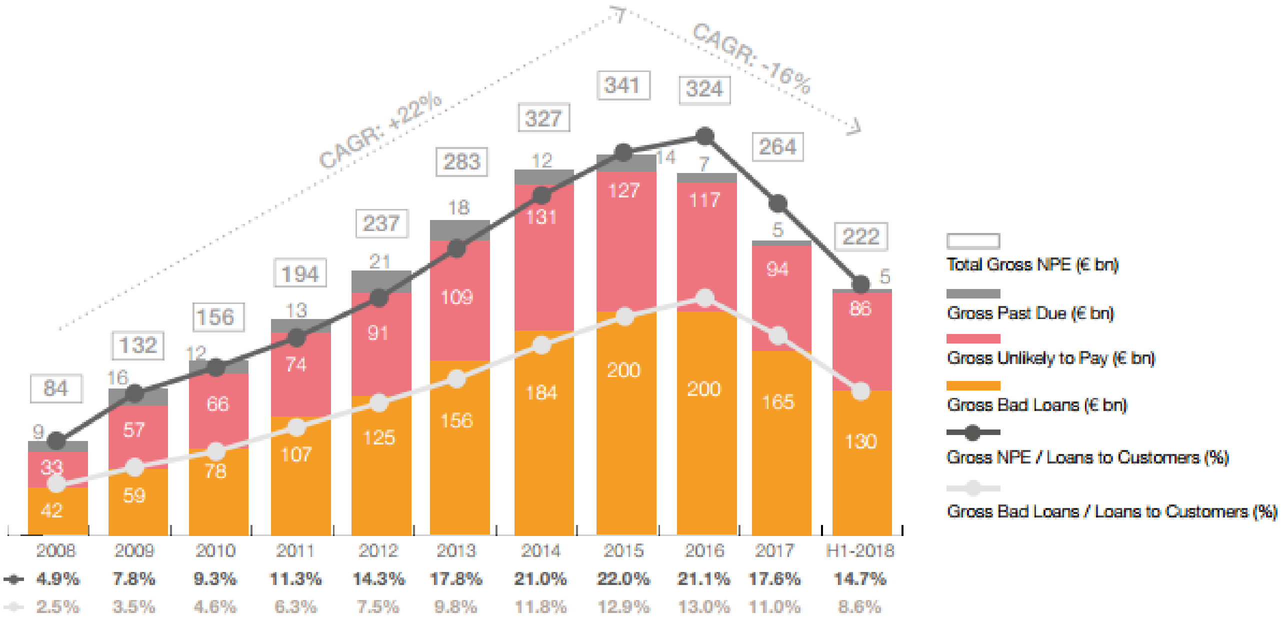



*Figure 1. Gross NPE and Gross Bad loans trend for the Italian market. The growth rate is expressed in terms of compound annual growth rate (CARG). Source: PwC, "The Italian NPL Market, entering a new era", December 2018*

From *Figure 1* it is clear the increasing trend in the total amount of NPE present in Italian banks' books since the beginning of the financial crisis in 2008 up to 2015, year in which it starts a decreasing path. This trend is inversely correlated with the Italian GDP level.

The reduction in the amount of NPL is due mainly to selling deals such as the bad loans securitization of €2.4bn GBV made by Unicredit in 2015 (Davi, 2015), or the bad loans portfolio of €10.8bn GBV sold to Intrum by Intesa Sanpaolo, together with 51% stake of their servicing platform for €500mln (Davi and Festa, 2018). It is important to notice that the selling of securitizations has a direct positive impact on credit recovery agencies (Centro Studi Unirec, 2019), since a part of the credit securities sold is injected in the market by third-parties transferees, meaning the buyers of already past due credits.

A recent update to the regulatory framework created new guidelines for the constitution of securitizations. It is represented by European Regulation 2401/2017 and 2402/2017 that entered in force in January 2019. The regulations define a set of criteria to identify less risky products, the so-called Simple, Transparent and Standardized (STS) securitizations. In this context investors can operate in a more transparent and risk-sensitive framework, leading to a disincentive to the creation of complex securitizations and favoring the constitution of a liquid market (D'Auria, 2018).

The reduction trend of NPL on the books of financial institutions continues its trend also in 2019. According to Il Sole 24 Ore that analyzed the data issued by Debtwire ABS NPL Database, in Italy from January to May current year, nine credit portfolios has been sold for a total amount of €5bn, while thirteen transactions are been carried over for a corresponding €29.9 bn, of which €24bn are UtP credits (Festa, 2019).

For what concerns the geographical distribution of NPE (*Figure 2*), the highest concentration is in Lombardy, accounting for almost one quarter of the total. This concentration is due to a higher general quantity of loans issued in Lombardy, since the gross bad loans ratio in the region is one of the lowest in Italy, equal to 6.6% (Pwc, 2018). This phenomenon is reproduced in all regions in the north area of the country, apart from Emilia-Romagna. An opposite situation is verified in

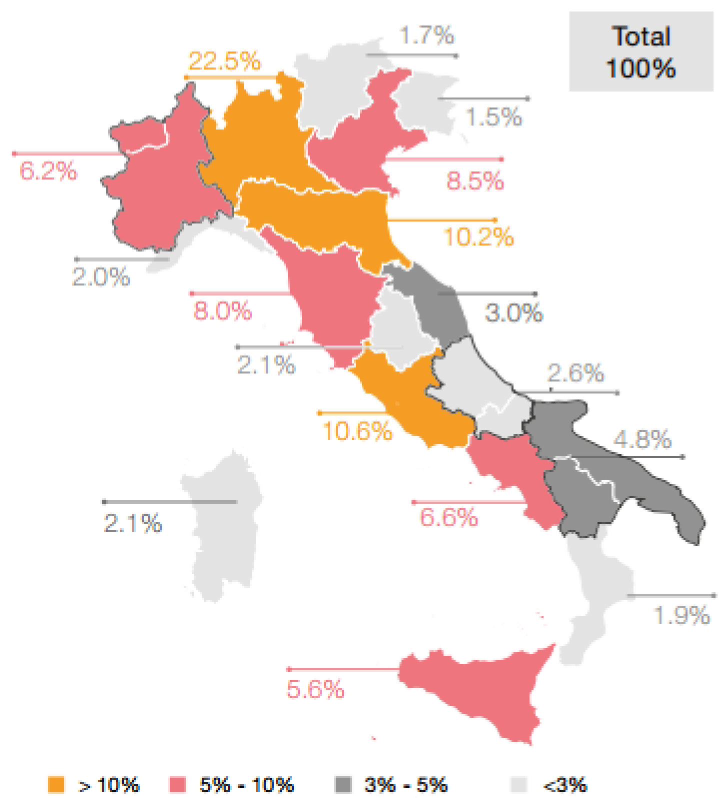



*Figure 2. Breakdown of Gross NPL divided by Italian regions. Source: Pwc, "The Italian NPL Market, entering a new era", December 2018*

central and southern regions, where the gross bad loan ratio tends to be higher (all ratios are between 10.1% and 13.3%, except for Lazio) but their volume accounts for a lower percentage of the total amount of gross bad loans in Italy (Pwc, 2018).

Different results are obtained for UtP. The UtP ratio for each region is generally lower (minimum of 2.6% in Lazio and maximum of 8.8% in Liguria) and more equally distributed between southern regions and those of the north. For what concerns the overall volume, Lazio and Lombardy are the

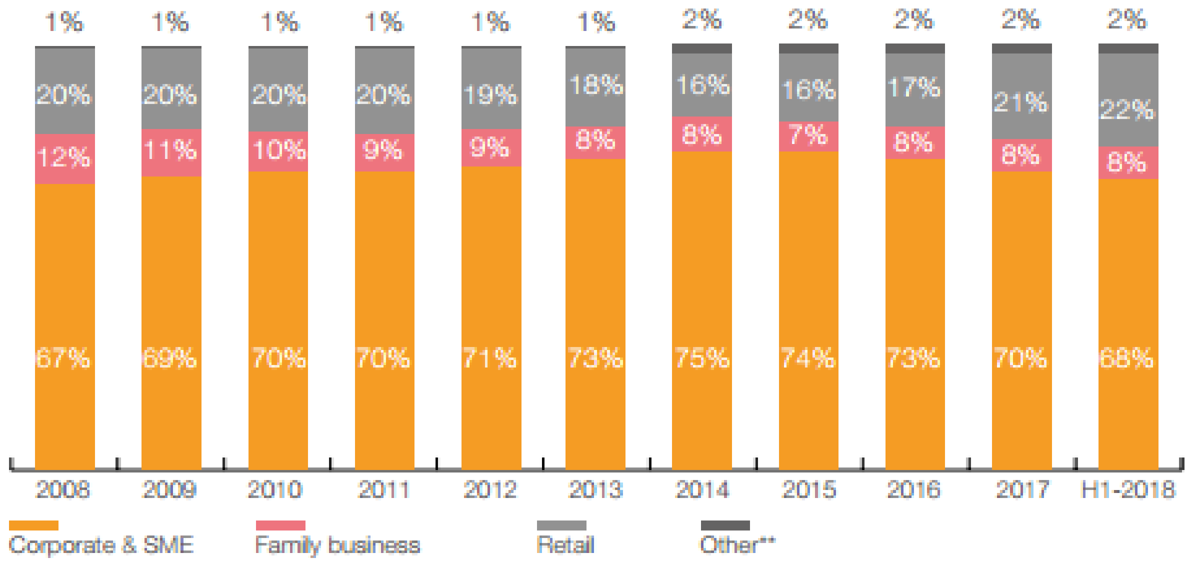



*Figure 3.Breakdown of Gross bad loans by counterparty (2018). Source: Pwc, "The Italian NPL Market, entering a new era", December 2018. **"Other" includes PA and financial institutions*

two regions with the highest volumes of UtP (equal to 14% and 26.3% respectively), and the total amount is mostly centered in the center-north area.

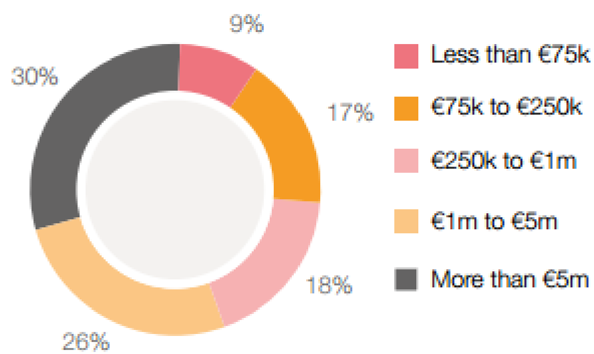



*Figure 4. Breakdown of Gross NPL by ticket size (2018). Source: Pwc, "The Italian NPL Market, entering a new era", December 2018*

The main counterparties of bad loans (*Figure 3*) are corporate and small-medium enterprises, with a share kept sufficiently stable since 2008 around the level of 70%, followed by retail clients for an average 20% of incidence. Family business together with PA and financial institutions have an impact of 10%. Furthermore, according to the Pwc report, in the first semester of 2018, up to 49% of total bad loans are secured, and correspondently 51% are unsecured loans (Pwc, 2018).

*Figure 4* shows the breakdown of the ticket size – i.e. the value to be recovered of a single credit position, intended as gross book value. More than half of the total NPL have a ticket size higher than €1mln, and 30% have a value higher than €5mln.

It is important to notice a massive presence of service credits linked to utility bills among positions dealt by credit recovery agencies (Faggella and Contini, 2018). In 2017 credit recoveries agencies associated to UNIREC, the main association of Italian credit recovery companies, managed a total number of 13.6mln non-performing service credits connected to TLC and utilities for an amount equal to €11.8bn, 16.7% of the total value entrusted. Also, electricity companies estimated in 2016 a total value of €1bn due only to late payments delinquency, with a level of closed electricity meters that touched a peak of 4.7% to retail and 5.8% to non-retail entities.

Finally, it is important to notice that, according to previous research, there is a correlation between macroeconomic factors and total amount of NPL in an economy. Tanasković and Jandrić (2014), through a static panel model analysis point out significative results:

- NPL ratio and GDP have a negative relationship, hence the improvement of the real economy generates a reduction in non-performing loan portfolios;
- Inflation does not affect NPL ratio;
- The development level of financial market has a negative impact on NPL ratio.

The results are confirmed by Messai and Jouni (2013). Furthermore, with regards to the unemployment rate, their research found “a positive and significant relationship with the ratio of non-performing loans at a level of 1%” as well as with the real interest rate, especially for loans with a floating rate (Messai and Jouni, 2013).

## 3. The Factoring Market

Together with financial institutions, another supplier of past due credits for credit recovery agencies is the factoring market. Factoring is internationally defined as a financial transaction and a type of debtor finance in which a company sells its credits to a specialized third party, called factor, at a discount. The goal of this transaction is to obtain immediate liquidity and additional services related to the management and accounting of the ceased credit (Banca Ifis, 2015).

There are three parties involved in this kind of transaction, i.e. the factor, the client company and the debtor (*Figure 5*). In Italy, the factoring contract is regulated by the Law 52 of 1991 (regarding the acquisition of companies' credits). The rule states that the factoring company must be a member of the proper professional register managed by the Bank of Italy. Furthermore, the client must be a firm or an autonomous professional and the credits that are sold must be certain, liquid and chargeable credits deriving from the operating activity of the client. It is important to highlight that the factoring is an operation that can regard only one credit or a basket of credits (article 3 of the law 52/1991).

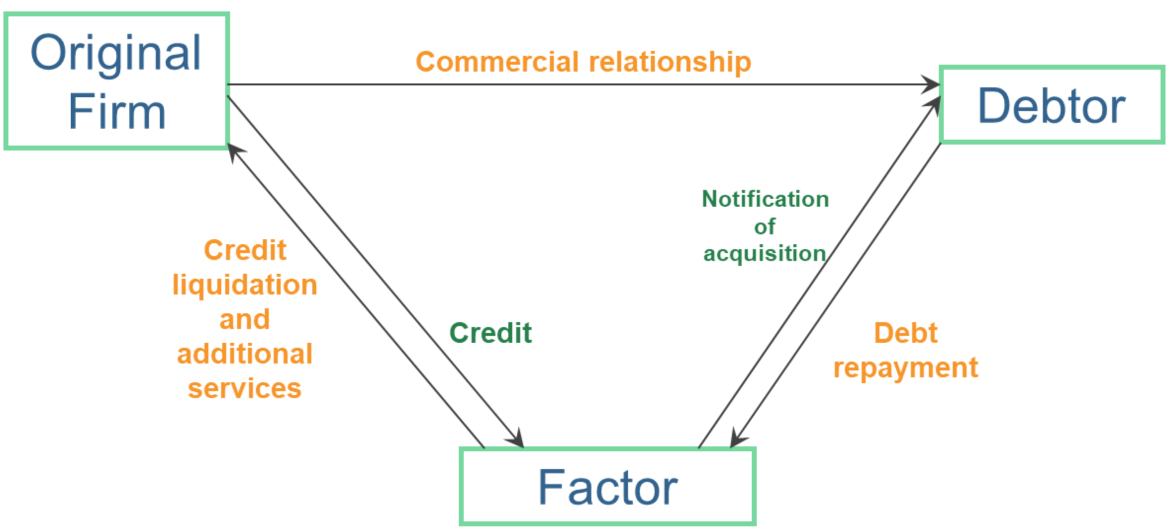



*Figure 5 The Factoring process and counterparties. Source: own elaboration.*

In such operation, the factoring company, i.e. the factor, takes in a part or all the counterparty risk connected to the position and is responsible to collect the proceeds from the debtor. The Italian jurisdiction offers two different types of factoring contracts and operations (Assifact, 2019):

- Pro soluto (i.e. non-recourse factoring): the factor takes in entirely the counterparty risk by fully purchasing the credit, usually with a higher discount rate due to the higher risk embedded in the operation. The client is obliged only to ensure the factor that the debt respects the criteria of being liquid, certain and chargeable;
- Pro solvendo (i.e. recourse factoring): the counterparty risk stays with the original creditor. This type of factoring can be seen as an anticipation on the accounts receivable (i.e., invoices) of the creditor company, similar to a secured borrowing. The factor may offer additional services such as being responsible for the accounting and the management of the credit.

There are also different categories of factoring depending on the type of relationship and regulating contract between the factor and the client:

- Full factoring: the factor has an agreement with the client such that it acquires all the commercial credits from the client on a rolling basis. It also includes accessory services such as the management of the working capital credits of the firm;
- Maturity factoring: the factor pays for the entrusted credits only at a specific date or at the maturity of the credit while the credit is ceased to the factor in a previous period. It is a form of credit recovery;
- International factoring: it is designed for foreigner clients operating with Italian firms or for Italian firms relying widely on export. The target of the international factoring is to facilitate export and import operations. With this type of contractual relationship, the factor may bear also the exchange rate risk, in case the currency of the importer or exporter is different from the currency of the client;
- Reverse factoring: in this case the debtor itself asks to the factoring company to provide liquidity to the creditor in exchange of the ownership of its credits. In some cases, it may be the debtor that provides the discount on the credit to the factor.

Factoring operations have a double advantage for the clients: it increases the available liquidity of the company while improving its financial statement, especially the working capital. By doing so, the factoring operation reduces the firm’s need for banking loans on the short term, increasing at the same time the credit score through a lower leverage ratio.

In Italy, factoring operations are broadly used, especially by companies operating in sectors where postponed payments are widely adopted and are a critical element for the main operations of the company. Those companies are usually SMEs of different business sizes.

The factoring market is on a growth path. As reported by Angelo Paletta on the article “the factoring market in Italy keeps growing”, this is partially the consequence of the reduction in the supply of credits offered to the corporate sector by financial institutions. The amount of banking loans issued to companies were compressed by €100 billion from 2011 to 2019, passing from €900 billion to less than €800 billion. On the same time the factoring market saw a reversal trend: from 2007 to 2017 the yearly turnover of factoring credits increased by €107 billion, a more then 100% growth rate. According to Assifact, the Italian trade association for the sector, the factoring business is now worth more than €123 billion, i.e. 13% of Italian GDP, with 30,000 companies participating in the market, most of them SMEs (Paletta, 2019).

Notice that the total turnover is a dynamic variable that measures the countervalue of the traded amount of factoring credits since the beginning of every year. The outstand amount, indeed, is a stock parameter that describes the total accumulated amount of factoring credits to be collected from the debtor.

Another element that explains the growth of the factoring market is the long time required for the PA to fulfil its obligations: according to the Ministry of Economics and Finance, the compound average number of days necessary for the PA to pay products and services provided by the private sector were equal to 55 days in 2016. This even if public entities are supposed, by the law, to pay its suppliers within 30 days after receiving the product or the service (the average number of days rises to 60 days for payments issued from the national health system).

For what concerns the composition of the factoring market, in Italy there are more than thirty big companies operating. Some of them are specialized in a specific sector and operate mostly with companies from that industry. The main players are: Banca Ifis, Factorit, Fidis, Mediocredito Italiano, Unicredit factoring and Credemfactor, among others.

Together with the main players, there are digital platforms of invoice trading that act as recourse factoring companies and compete directly with the traditional factoring entities. These are Credimi, Fifty Finance Beyond, FinDynamic, Modefinance and Workinvoice. The competitive advantage of these digital start-ups is that their digital infrastructure and a lean organization allow them to target smaller companies, that usually do not have access to the traditional factoring channels (Angelo Paletta, 2019).

Mr. Fausto Galmarini, the president of Assifact, said on the annual meeting of the association that the Italian factoring market is the third biggest market in Europe and the fourth globally, after China, France and UK (Assofin, 2019).

| | Dec. 2015 | Dec 2016 | Dec 2017 | Dec 2018 | *Delta %* |
|---|---|---|---|---|---|
| **Total Turnover** | **184,796,669** | **202,402,830** | **221,597,438** | **240,038,627** | ***29.89%*** |
| Pro solvendo | 59,191,993 | 55,691,511 | 57,659,684 | 58,784,323 | *-0.69%* |
| Pro Soluto | 125,604,676 | 146,711,319 | 163,937,754 | 181,254,304 | *44.31%* |
| **Outstanding** | **57,493,137** | **61,009,983** | **62,343,204** | **67,688,862** | ***17.73%*** |
| Pro solvendo | 20,741,997 | 18,287,640 | 19,403,499 | 18,516,663 | *-10.73%* |
| Pro soluto | 36,751,140 | 42,722,343 | 42,939,705 | 49,172,199 | *33.80%* |
| **Turnover YoY%** | | 9.53% | 9.48% | 8.32% | |

*Table 1. Factoring market trend in Italy. The total turnover refers to the total traded amount of credits in the factoring market since the 1st of January, while the outstanding amount is a stock measure describing the actual quantity of factoring credits to be recovered. Source: own elaboration of data from Assifact (Assifact, 2015-2019).*

The trend of the Italian factoring market is described in *Table 1*. As previously described, the total turnover identifies the whole amount of traded credits from January to the end of December. The outstanding sum on the table identifies the total amount of purchased credits unpaid until the specific date.

*Table 2* and *Figure 2* confirm an increasing trend from December 2015, for both the turnover and the outstanding amount. In detail, the turnover has increased by a higher amount if compared to the outstanding amount (+34.95% vs. 15.10%), signalling a market with a low rate of non-performing credits.

The difference between the increase of the turnover and the increase of the outstanding amount, in fact, confirms the fact that the factoring credit market has a higher quality if compared to the financial credit market. According to the Assifact, only 5.23% of factoring credits are past due positions, versus the 10.4% of banking assets, while defaulted credits are only 2.25% against the 5.6% average of the banking sector (Assifact, June 2019). Furthermore, the yearly average increase in the turnover is around 9% and is stable since 2017.

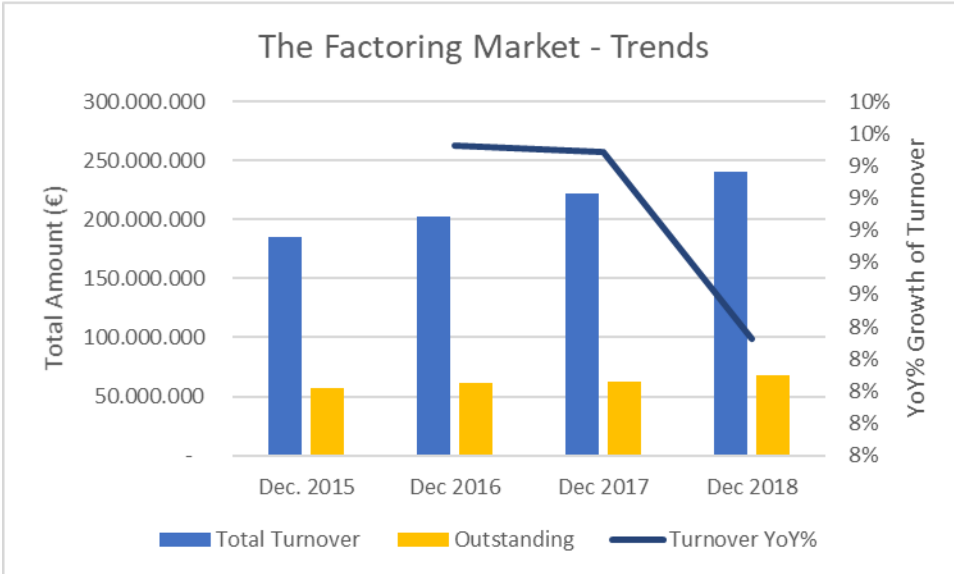
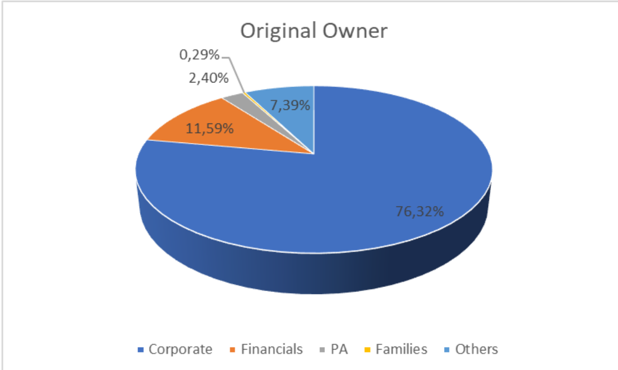



*Figure 6. Factoring market trend in Italy. Source: own elaboration of Assifact (Assifact, 2018)*

As shown by *Table 1*, in the last years, factoring companies focused their operations on the non-recourse factoring. The category saw an increase of 44.31% from December 2015 to December 2018. In the same timeframe, the recourse factoring decreased by -0.69% (*Figure 6*). This trend impacts on the activity of credit recovery agencies, that participate in the market by purchasing past due pro-soluto credits or by managing the past due factoring credits for third parties. This trend is also the consequence of the fact that companies with past due credits tend to sell their credits with the factoring formula (Assifact, 2019)

Considering the operating sector or the juridical nature of the original owner of the credit, i.e. the client, in 2018 two thirds of the factoring credits were originally owned by corporate entities (of which 47% are SMEs), followed by financial entities. Another important category is "others" that accounts for 7,39% of the total number of clients and includes NGO, professionals and other unclassified entities (*Figure 7*).



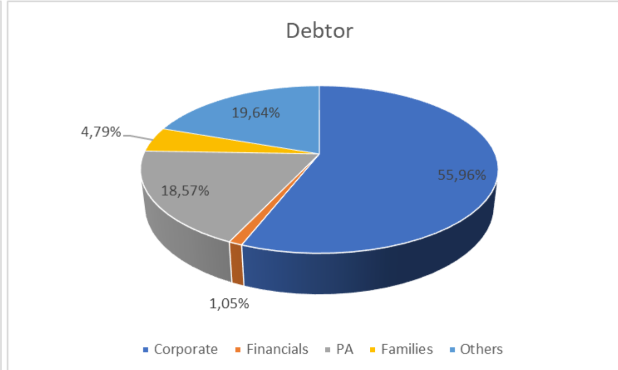



*Figure 7. Distribution of the factoring activity by Original owners and by Debtor. Source: own elaboration on data of Assifact (AssIfact, 2018).*

Taking into account the nature of the debtor, 55.96% of the total are corporate entities, while the PA weights for around 19%, as NGO and professionals. As reported by Assifact, one third of credits whose debtor is the PA are past due credits, and 67.64% of them are past due from more than a year (Assifact, 2018).

Finally, according to a research made by Assifact and the business school SDA Bocconi, the Italian regions with a higher concentration of factoring activities are: Lombardy, Piedmont, Veneto, Emilia Romagna, Tuscany, Lazio and Campania, even if the data collected is from 2006 (A. Carretta, 2009). All other regions had an amount that accounted for less than 2% of the total turnover. The highlighted regions are the geographical areas where the economic activity is concentrated alongside the Peninsula.

## 4. Overview of the Credit Recovery Market in Italy

In 2018, the Italian Chamber of Commerce listed 952 companies operating in the credit recovery sector in Italy (primary and secondary Ateco code 82.91.1). According to UNIREC[2], the Italian association of credit recovery agencies, this means an increase of 22% in comparison to the previous year, 169 in total units.

Companies operating in the credit recovery sector are mostly in the form of limited liability companies (Srl), accounting for 715 units (75,11% of total). This is followed by 121 limited partnerships (Sas) and by Joint Stock Companies (SpA), equal to 61 units. Joint stock companies constitute the main players in the market. In fact, in 2017, companies in the form of SpA produced 51% of the total revenues of the sector. Limited liability companies, i.e. Srl, generated 47% of total revenue, while only 2% of the revenues is created by companies in the form of limited partnership, consortiums and others (*Table 2*, Centro Studi UNIREC, 2019).

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Δ on PY | % on total (2018) |
|---|---|---|---|---|---|---|---|---|
| **SpA** | 37 | 26 | 35 | 46 | 56 | 61 | 5 | 6.41% |
| **Srl** | 638 | 631 | 633 | 594 | 578 | 715 | 137 | 75.11% |
| **Sas** | 187 | 164 | 159 | 119 | 104 | 121 | 17 | 12.71% |
| **Snc** | 56 | 48 | 45 | 36 | 33 | 40 | 7 | 4.20% |
| **Consortiums, others** | 9 | 9 | 19 | 13 | 12 | 15 | 3 | 1.58% |
| **Tot. Companies** | **927** | **878** | **891** | **808** | **783** | **952** | **169** | **100.00%** |

*Table 2. Distribution of companies with Ateco Code 82.91.1 by legal status (no.). Source: own elaboration on data present on "Credit Protection Services IX Annual Report", Centro studi UNIREC, 2019.*

For what concerns corporate metrics, the sector has seen an increasing trend in the total revenues reaching €1068mln in 2017 and overpassing the peak of €916mln in 2015. Furthermore, in 2017, the revenues deriving from credit recovery activity alone[3] amounted for a total of €1027mln, accounting for 96% of the total revenues (*Figure 8)*. Up to this date, data on 2018 is not disclosed yet.

[2] The association gathers together more than 200 companies operating in the credit collection industry, equal about 80% of the sector.
[3] Revenues from the selling of commercial information, re-marketing etc. are included under the item "other revenues" and excluded from revenues from credit recovery activities alone.

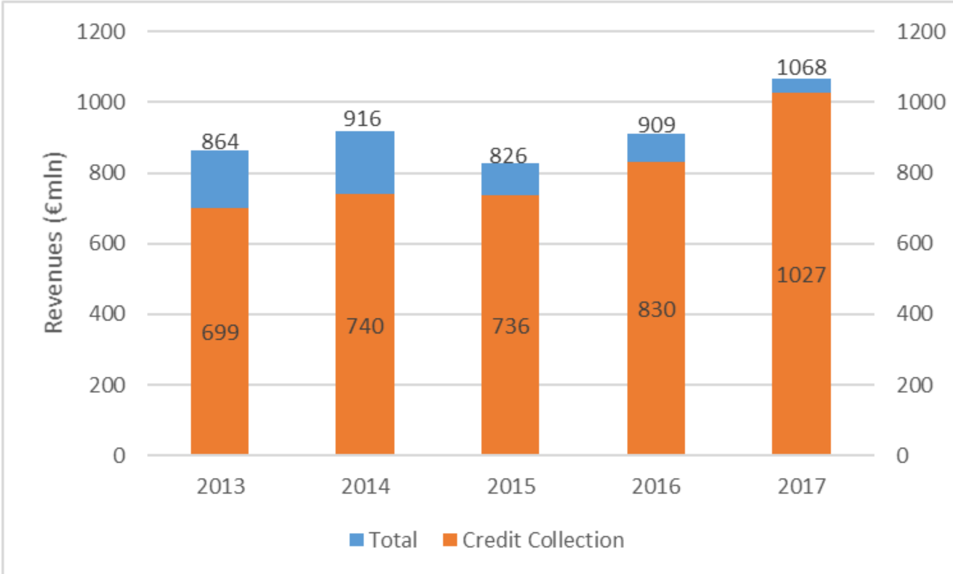



*Figure 8: Revenues from Credit Collection. Source: own elaboration on data present on "Credit Protection Services IX Annual Report", Centro studi UNIREC, 2019.*

### a. Collection Trends in the Italian Market

It is possible to identify three macro-business areas within the credit collection market (Centro Studi UNIREC, 2019). These areas are divided according to the nature of the owner of the credit.

In this regard, Third-party (3$^{rd}$-party) credits are those credits whose collection is given to the recovery company by an external client owning the asset. The external client can be the one that originated the credit at first, and the credit is referred to be a 3$^{rd}$-party Originator credit. On the other hand, in case the client has come to be the owner of the security in a second moment, the credit is classified as a 3$^{rd}$-party Transferee credit. Examples of originators are banks or utility companies, while a transferee can be an investment fund that bought securitizations from a bank.

The third macro-business area within the credit recovery market is called Own Credits. In this case, the credit collection company itself has the property of the credit. The ownership can be reached either through the purchase of securitizations or other forms of credit acquisition, or through its origination by a firm belonging to the same group of the credit recovery company. It is important to notice that 3$^{rd}$-party Transferee credits and Own Credits have benefited from the increase in NPE transfers by Italian financial firms over the past few years (Centro Studi UNIREC, 2019).

In 2018, UNIREC associated companies managed 38.73 million cases of 3rd-party Transferee and Originator credits, of which 12.38 million units have been collected. The corresponding amount is €82,341 million entrusted versus €7,835 recovered, meaning that securities with a smaller nominal value are easier to recover. According to UNIREC (Centro Studi UNIREC, 2019), this phenomenon is due to the presence of a growing number of collection assignments for NPLs accumulated in the financial statements of banks, that have a higher average value and become more difficult to recover over time.

| | Entrusted | | | Collected | | |
|---|---|---|---|---|---|---|
| | Unit (no./000) | Amount (€ mln) | Amount Δ% on PY | Unit (mln) | Amount (€ mln) | Amount Δ% on PY |
| 2014 | 40,603 | *56,235* | *16.00%* | 16,817 | *9,672* | *1.7%* |
| 2015 | 38130 | *58,975* | *4.9%* | 15,605 | *9,419* | *-2.6%* |
| 2016 | 35,654 | *69,377* | *17.6%* | 12,187 | *8,191* | *-13.0%* |
| 2017 | 35,050 | *71,451* | *3.0%* | 12,047 | *7,470* | *-8.8%* |
| 2018 | 38,730 | *82,341* | *15.2%* | 12,384 | *7,835* | *4.9%* |

*Table 3. 3rd-party cases, entrusted and collected. Source: own elaboration on data present on "Credit Protection Services IX Annual Report", Centro studi UNIREC, 2019*

As specified by UNIREC in its annual report, among 3rd-party credits, the Originator cases are the most significant in volume, being equal to 82% of the total number of entrusted cases (versus an 18% of 3rd-party Transferee cases), and 93% of those collected. But we have a different composition if we consider the total amount of credits. In fact, the total value entrusted is composed of 52% of 3rd-party Originator credits, and of 84% if we consider the amount collected.

This difference is caused by the heterogeneous composition of portfolios of the two parties, i.e. the difference between 3rd-party Originator and 3rd-party Transferee credits. In fact, 3rd-party Originator credits include a higher portion of securities originated from utilities, and hence with a lower average amount. For the Originator's category the average value of a credit is equal to €1,346. On the other hand, 3rd-party Transferee credits tend to be of financial and banking type, with an average amount equal to €5,673 (Centro Studi UNIREC, 2019).

For what concerns the Own credits business area, recovery agencies that are part of UNIREC in 2018 bought 1.27 million credit securities, for an amount equal to €3.85 billion. Of those, 786 thousand have been collected, for a corresponding amount of €364 million. At the end of 2018, credit portfolios of UNIREC's agencies presented 5,986 million units of credits with a corresponding value of €19.835 billion (Centro Studi UNIREC, 2019).

Regarding the geographical distribution of the debtors of 3rd-party credits, it is similar to the overall distribution of banking NPLs in the country. In fact, looking at the number of entrusted cases, we have a higher concentration in Lombardy, Lazio, Campania and Sicily (*Figure 9*). An almost equal distribution in percentage terms is shown for the number of collected credits (Centro Studi UNIREC, 2019).

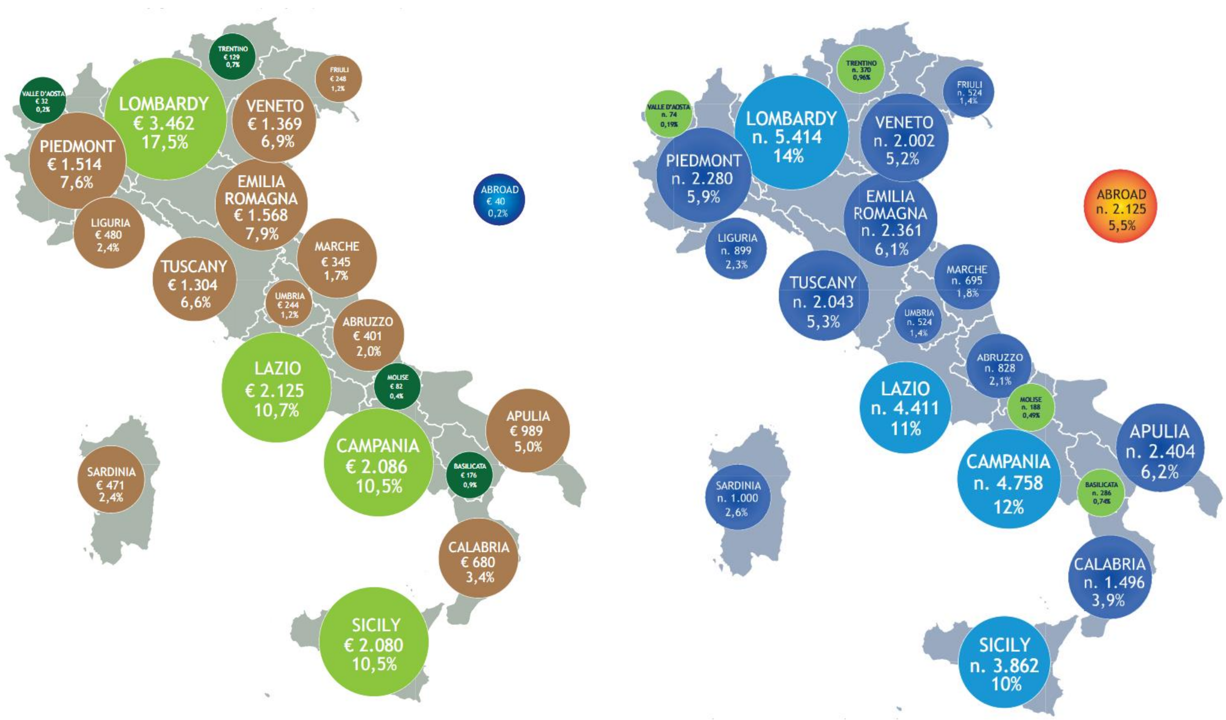



*Figure 9. On the right: 3rd-party cases entrusted divided by Region (n/000 and % weight). On the left: Geographical distribution by Region of the Own/C Portfolio Amount (€ /mln). Source: Unirec Associated Companies, Centro Studi UNIREC data processing, May 2019.*

The geographical distribution differs if we consider the amount of the entrusted 3rd-party credits. In particular, northern and central regions tend to have a higher average ticket size of credits with regards to southern regions and islands.

Furthermore, it is possible to highlight a positive incidence of the available income of regions on the percentage of collected credits in each area. Regions with a higher average income show a higher level of recovered cases (Lombardy, Liguria, Alpine regions), while those with a lower income displays a lower performance, such as Apulia, Calabria and insular regions (Centro Studi UNIREC, 2019).

Own credits portfolio of companies associated to UNIREC in general reflects the geographical distribution of 3rd-party credits. The main differences in the distribution between 3rd-party credits and Own credits is a higher concentration in Lombardy, where it reaches a weight of 17.5% of the total amount of credits, as well as in Sicily and Piedmont (UNIREC, 2019).

### b. Players of the Credit Recovery Market

Another way to analyze the composition of the credit collection market in Italy is to consider the sector where the credits were initially originated. In this perspective, UNIREC offers a detailed analysis focusing on the three categories previously discussed (3rd-party Originator and Transferee credits and Own credits).

It is important to specify that the following analysis is based on surveys issued by UNIREC to its associates, of which 70% provided an answer (Centro Studi UNIREC; 2019).

The first category to be analyzed is the 3rd-party Originator credits. In this case the sector of provenience of the credit obviously agrees with the one of the clients of the collection agencies.

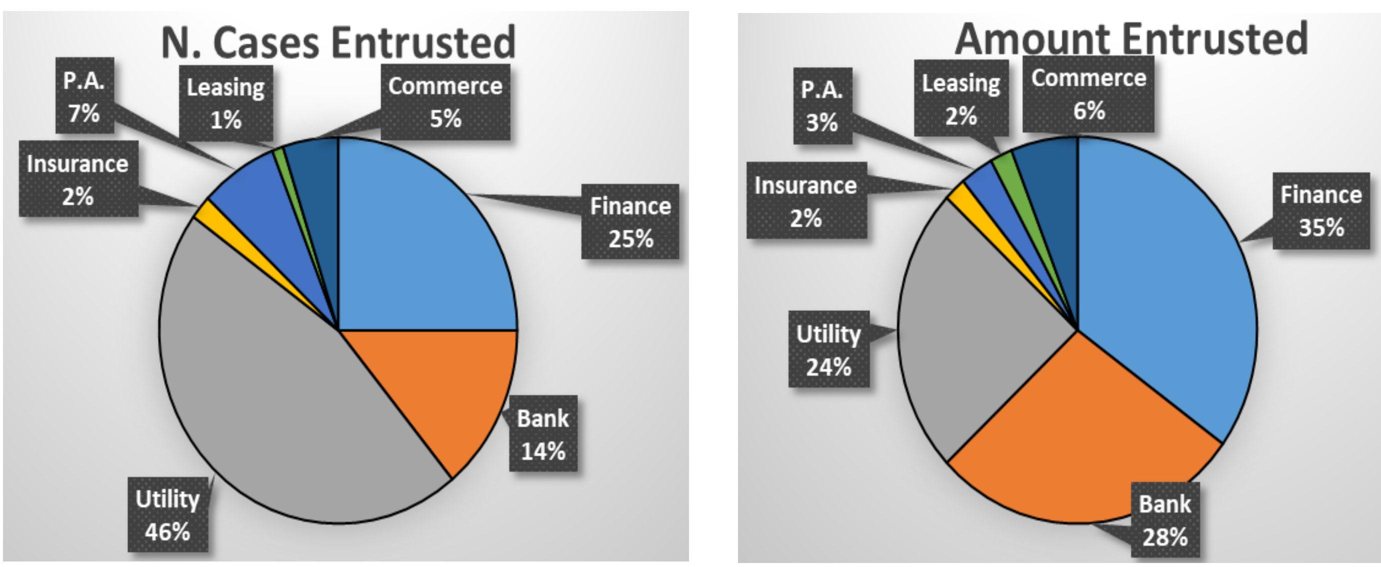



*Figure 10. 3rd-party credit portfolio breakdown by sector. Source: own elaboration on data present on "Credit Protection Services IX Annual Report", Centro Studi UNIREC, 2019.*

In terms of number of cases entrusted, the most relevant sectors of origin are those of finance, banking and utility companies, that together account for 85% of the total cases assigned (*Figure 10*). These three sectors maintain their leading role if we consider also the amounts entrusted, being around 87% of the total, but in this case the weight of each sector changes. In fact, the utility sector, that supplies the higher number of cases (46% of the total), accounts for 26% of the total amount entrusted. A different proportion is presented for both the financial and banking sectors, that have a higher weight if we consider the total amount entrusted (35% and 28% respectively) but a lower number of cases (25% and 14%). The average value of banking credits entrusted is equal to €2,118, versus the €1,488 of the financial sector and €546 of utilities.

Other minor sectors where 3rd-party Originator credits are created are insurance, commerce, leasing and the public administration. These sectors together account for 15% of cases entrusted, and 13% of the total amount.

It is important to notice two further breakdowns in the category of financial and banking debts. In particular UNIREC offers the distintion between pre-DBT[4] and post-DBT credits for these two categories. In 2018, pre-DBT credits accounted for a 81% of the total in the banking sector and 77% in the financial sector if we consider the total number of cases, while it represents 48% and 42% respectively considering the total amount. The relevant fact is the increase in percentage terms of pre-DBT with regards to the previous year, when they accounted for 67% of total cases and 20% of the total amount[5]. As stated by UNIREC in its report, "the increase in percentage weight of pre-DBT compared to post-DBT entrusted in outsourcing could be seen as a sign of greater attention by the clients in managing risk, in order to prevent further deterioration of credits" (Centro Studi UNIREC, 2019).

Looking at the 3rd-party Transferee credits, as for the Originator scenario, most cases were originated from the financial (36%), utility (30%) and banking (18%) sectors, that together account for 84% of the total cases entrusted. If we consider the total amount of the credits, these three sectors together have a weight of 90% of the total (60% originated by the financial sector, 26% by the banking sector and 6% by utility companies).

Furthermore, 3rd-party Transferee credits have a higher average value than the Originator credits (€5,584 versus €1,053). In fact, the total amount entrusted is €30.1 billion for Originator credits,

---

[4] Days beyond terms (DBT) is a commonly used business credit term that indicates how long a business has taken to pay its invoices beyond the agreed payment terms. On the analysis made by Centro Studi of UNIREC, the term is used to indicate, for the pre-DBT category, "items which, even though there is a delay in instalment repayments, […] there is still a possibility of the loan being refunded in instalments" (Centro Studi UNIREC, 2019), while for the post-DBT the counterparty have to repay the whole amount of the loan in one lump sum, due to a longer past due period.

[5] In UNIREC's analysis, before 2018 the financial and banking sectors were grouped together.

and €38.3 billion for Transferee ones, but the number of cases are higher for the first category (28.6 million cases of 3rd-party Originator credits versus 6.9 million 3rd-party Transferee).

The higher average value of 3rd-party Tranferee credits can be explained by a double effect of a lower presence of credits generated by the utility sector and a higher aging of credits (Centro Studi UNIREC, 2018). In fact, more than 60% of 3rd-party Tranferee credits from the financial and banking sectors are past due by more than 3 years. The percentage rises to 94% if we consider credits from utility companies. Also, it is important to notice that there is a positive correlation between the credits' average value and their aging, but a negative correlation between the time it is past due and the collection performance (Centro Studi UNIREC, 2018).

A different situation is displayed if we consider the Own credit portfolio. For this category, 50% of the amount of credits derive from the banking sector and 38% from the financial sector. Other credits have a total weight of 11% in the amount, even if they account for 66% of the total number of credits, and they comprehend credits deriving from utility, insurance and commercial sectors. The average value of credits deriving from banking and financial sectors are of €8,619 and €8.588, similar to 3rd-party Transferee credits (Centro Studi UNIREC, 2018).

Finally, it is relevant to notice that 99.6% of the number of Own credits are unsecured credits and 82% are credits issued to consumers and retail (Centro Studi UNIREC, 2018).

The scenario presented until here sums up the composition of the credit collection market in Italy and how NPL and past due positions are distributed across the country. To have a clearer overview of how the credit collection market works, it is useful to analise the process of credit recovery and its associated costs.

## 5. The Judicial Procedure

The judicial recovery is a legal action that consists of referring an unpaid debt to a competent court in order to recover it. The article 2740 of the Italian civil code is the sets of rules for the legal process. The article states that “the debtor fulfils its obligations with all of its past and future goods”.

The recovery process has specific requirements for each of its stages. In Italy, to start the legal action the creditor needs an enforcement order (*titolo esecutivo* in the Italian law). The most common enforcement order used is the cease and desist letter (*decreto ingiuntivo* in Italian law, ex art. 633 c.p.c.), obtainable from a judge by presenting specific documents. These required documents must demonstrate that the past due credit is *certain*, meaning that it is clear in its contents, *liquid*, in the sense that it concerns a specific object (for example, a specific amount of money or an unpaid delivered good, if it is a commercial credit), and *chargeable*, meaning that the right of requiring the payment has not expired (art. 474 c.p.c.). The article further specifies a list of possible documents comprehending “sentences […], notarized private agreement […], bills of exchange or other credit securities […] and acts received by notaries or other public authorities” (art. 474 c.p.c.). Together with the general files, the creditor must attach a previously sent injunction to perform letter (*diffida ad adempiere*, in the Italian Law system, art. 1454 c.c.). The injunction to perform letter is a registered letter with return receipt reporting the origin of the credit, any payments by the debtor, and the payment method with which the debtor must close its position in a term of usually 15 days.

The cease and desist letter obtained by the judge can be of temporarily enforcement (*provvisoriamente esecutivo*, in the Italian law, art. 642 and 482 c.p.c.) or non-temporarily enforcement, depending on the strength of the probatory documents. In the first case there is an immediate notification of the cease and desist letter and the debtor has forty days to oppose to the order of the judge, while in the second case it is necessary to wait for the reception of the notification before start counting the required forty days.

If in the forty days following the reception of the cease and desist letter the debtor poses no opposition or neither closes the position, the creditor may ask for the issuance of the writ of execution (*atto di precetto*, in the Italian law, art. 480 c.p.c.). With this instrument, the creditor requires the payment within ten days from the notification of the writ. If there is still no response from the debtor, the creditor can demand the foreclosure of the debtor assets once it is verified that the holdings of the debtor are enough to repay the debt. In case the debtor is destitute, the only possible solution is to retry the judicial procedure after some years (N. Canestrini, 2018).

Furthermore, in case the debtor decides to resort to the legal opposition, it starts a civil trial that leads to a longer and more expensive process (N. Canestrini, 2018).

The cost of the legal process varies according to the amount to recover and to the point of the procedure in which the amount is recovered. A first cost item is the lawyer's tariff, that is variable. Even if in the Italian jurisdiction the charge for legal services must lay in a pre-specified range (Law n. 223, 2006), it will be the lawyer to set the price analyzing the specifics of the case. A second cost are the associated taxes (Law n. 488, 23rd December 1999). They are null for the recovery of an amount lower than €1,033. For sums exceeding this benchmark, it is required a payment that starts from €62 (for a sum to recover that lays between €1,033 and €5,165) up to €930 (if the amount to recover is higher than €516,457). The creditor may have then other accessory expenses related to the process.

For example, according to N. Canestrini, to recover a credit which face value is between €5,200 and €26,000 it is required €278 of associated taxes, €27 of a stamp duty (*marca da bollo* in Italian) and around €540 for the legal assistance, with an additional +22% VAT, +15% for general expenses and a minimum of +4% for the social security system. Summing them together, the minimum total cost is around €1100. Furthermore, other variable costs may be added such as: asset investigation (around €250), notarial costs for the documents authentication (€80 on average) and costs connected to the tender in the case of the underlying of the foreclosure being a real estate (N.Canestrini, 2018).

On the other hand, the high costs of the legal action in Italy are not correlated with efficiency. As reported by Banca Ifis (Banca Ifis Area NPL, 2016) the average time needed to complete a legal credit recovery lies between 48 to 90+ months (with an average of 1210 days for the civil trial only), versus the European average of 16 to 20+ months. The slowness of the legal process impacts also on the price received for an NPL selling, as reported by Banca d'Italia, that highlights a decrease of 5% of the price of the security per each additional year required for the legal recovery (Banca d'Italia, 2017).

Due to high costs and the long process connected to the judicial action, today companies, banks and PA entities tend to focus primarily on extra-judicial recovery. Usually, only after a first out-of-court attempt to recover a past due debt, and once the credit is verified to be recoverable (due to an asset investigation that verifies the economic condition of the debtor), the creditor decides to undertake a legal trial.

### a. The Extra Judicial Process

There are different reasons that make the extra judicial credit recovery more efficient and cost saving for the creditor, especially for smaller entrusted amounts. In fact, the non-judicial process tends to be faster if compared to the legal action. According to Gainpaolo Luzzi, credit recovery agencies provide a conclusion for the dossier in a minimum of 25 and a maximum of 125 days. Furthermore, the main expense for the creditor is a percentage of the sum recovered by the agency. Finally, in case of negative result and under certain conditions (art. 101 TUIR, 2004), the credit agency may certify that the credit is unrecoverable, such that its amount can be accounted as a cost by the creditor with a consequent benefit in terms of taxes expenditure (Fisco Oggi, 2019).

A general overview of the recovery process is offered by Gianpaolo Luzzi (G. Luzzi, 2017). According to the author, creditors usually entrust many credits at time to the recovery companies. Because of this, most agencies have a specific division that operates an initial screening on the dossiers, prioritizing the recovery of some securities depending on its specifics. The first criterium considered is the geographical position of the debtor, since most credit recovery companies operate exclusively or more efficiently in limited geographical regions. Apart from this criterium, more recently past due credits and those with a higher unpaid capital amount are preferred to others (G. Luzzi, 2017).

At the end of this initial operation, credits are assigned to each operator. The operator must then verify the presence of the required documents and examine then. The attachments should include the contract that originates the credit, the connected invoices and previous payments, plus any other relevant document that can facilitate the activity of the agency.

This step is followed by the creation of a recovery plan. At this point, the operator should analyze several elements contained in the documents. In particular, contact details of the debtor as well as the generic information about the security are key elements for the following phases of phone and home collection.

The phone collection means that the operator telephonically contacts the counterparty in order to discuss the ways to recover the amount owed by the debtor. Indeed, in the home collection an external collector physically visits the debtor's domicile. While all agencies operate with the home collection, not all of them use the phone collection (G. Luzzi, 2017).

For the sake of our analysis we will consider the case where both methods are applied. In this scenario, the home collection is complementary to the phone one. Agencies usually recognize to the collectors a percentage of the amount recovered, reducing the margin for the company. Because of this, credit recovery companies focus their activity on the phone collection in order to increase their margins (G. Luzzi, 2017).

At the moment of the first contact, to understand the reasons that can lead to a past due position is vital. According to Luzzi (G. Luzzi, 2017) there are five main causes of this phenomenon:

1. Administrative errors: the creditor does not clearly indicate to the debtor how to pay the sum;
2. Dispute concerning the terms of the contract: this is particularly true for consumer credits. Usually, when the debtor starts the dispute, he/she immediately stops any payment, causing a damage for the lending financial entity.
3. A sudden problem in the financial situation of the debtor: this is true mostly for consumer and commercial credits and mortgages.
4. A wrong evaluation of the debtors' financial position: this is a common situation for commercial credits, consumer credits, current account openings and for utility contracts, where no or low verification is required.
5. Fraud, common mostly for consumer, commercial and banking credits.

Understanding the causes that generate the past due position is useful to conduct the following steps of the recovery process.

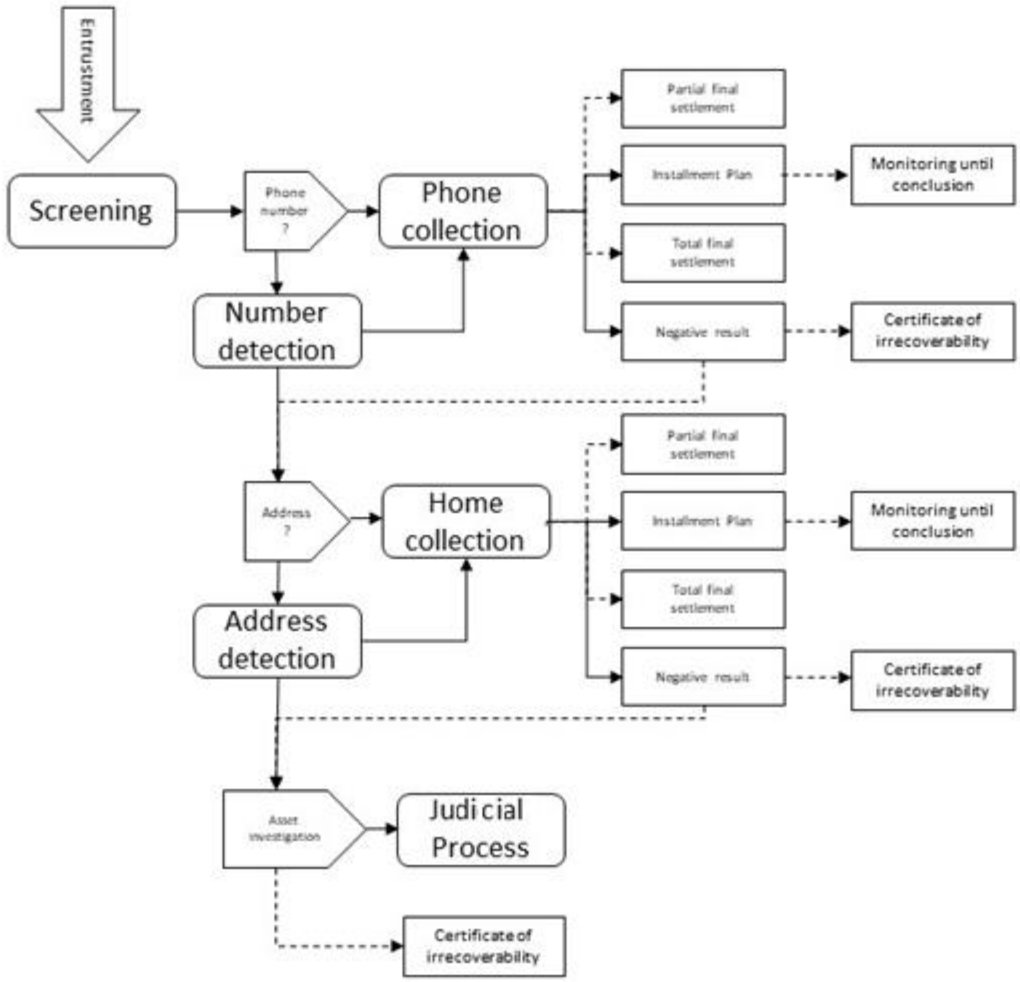



*Figure 11. Diagram of the non-judicial recovery process. Source: Own elaboration.*

The process is described by the diagram in *Figure 11*. During the verification, the operator checks the presence of a phone number. Once the debtor number is verified, the operator contacts the debtor and discusses a way to settle the payment. The ideal goal for the operator is to reach a full repayment through a total final settlement operation or an installment plan, but in case of a verified problematic financial situation of the debtor, the agency may concede a partial final settlement or a partial installment plan. In case one of these positive results is achieved, the credit agency provides to collect the amount and to transfer it to the creditor, keeping its margin.

In case of negative result, the operator may resort to an external collector to start the home collection. It is worth to start the home phase when the debtor operates in bad faith or cannot be found only with the telephone number. If the debtor is in a problematic financial situation and the operator expects the debtor to be unable to repay, the agency may, under certain conditions specified by art. 101 TUIR of 2004, issue to the creditor the certificate of irrecoverability.

In the home collection, the external collector persecutes an approach similar to the operator of the phone collection, by personally discussing with the debtor viable solutions to close its position. In case the address is not transmitted by the creditor, the operator may ask for an address verification. Due to its cost, this information is requested only if the amount to recover is above a certain limit and is considered likely to be recovered.

The possible results of the home collection are the same as for the phone contact, with an additional opportunity to collect more information about the debtor's financial situation. If the debtor shows no intention to repay its debt, the external collector may suggest to the credit agency to initiate an asset investigation in order to pursue a judicial attempt of recovery, or alternatively to issue a certificate of irrecoverability, depending on the financial situation of the debtor and under the conditions specified by art. 101, TUIR.

If an asset investigation displays a favorable scenario for the judicial action, the recovery company may, in agreement with the creditor, issue a cease and desist letter. If the result of the asset investigation is negative indeed, the company may issue the certificate of irrecoverability under the request of the creditor and under the conditions specified by art. 101, TUIR.

Considering all of its possible steps, the costs associate to the non-judicial recovery varies widely depending on the length of the process itself. From the creditor point of view, at the moment of entrustment the owner of the credit is required to pay a fixed sum per dossier. This amount varies according to the type of contract proposed by the recovery agency, the type of credit to be recovered and the total number of credits that is entrusted in a tranche. According to G. Luzzi, the initial payment varies from zero up to two hundred euros, but the average value is usually of 30€ per dossier (G.Luzzi, 2017). Another option is for the creditor to subscribe a plan with the recovery agency. Doing so, the creditor pays a monthly, semesterly or yearly fixed amount and has a maximum number of dossiers to entrust for the selected period.

There are further accessory costs that may be charged to the client. Some of them are the number detection, the injunction to perform letter or the real estate verification, among others.

Finally, after a positive result of the collection, the creditor pays to the credit recovery agency a percentage of the recovered amount. This margin varies among companies, but it usually stays below the 20% level (G. Luzzi, 2017). This percentage on the recovered amount is the main source of income for credit recovery companies.

From the recovery agencies point of view, the expenses are the whole accessory costs together with the labor expenses. Furthermore, in case the company recurs to the home collection, the collector receives 10% to 15% of the sums recovered, reducing the margin for the company. Possible accessory costs are:

- Financial investigation, indicating if and the entity where the debtor has open accounts and its consistency. It can cost up to €200;
- Salary investigation, indicating the job position and salary of the debtor. It can cost up to €80;
- Number and address detection, that can be of around €10;
- Real estate verification, of around €10;
- Automobile property verification, that varies from €5 to €45;
- Verification of previous unpaid positions, that costs up to €10 through the Cribis platform.

In the best scenario where the credit is recovered after few calls from the operator, the credit agency recovers the sum with almost no expenses. But in case the recovery is made difficult, the company may spend a large amount of resources without the certainty of an income. Considering this, it is hard to estimate the costs of the recovery.

Once an overview of the past due credits' market is offered, both from the sell side (financial entities and factoring entities) and the buy side (credit recovery agencies), we are able to start describing our sample to dive deeper into the model.

## 6. The Sample

The sample is offered by Teseo Srl, a mid-size credit recovery agency. The company is based in Padua and operates in the whole Italian territory. The agency, together with the activity of credit recovery for external clients, owns an NPL and past due credits portfolio made of securities acquired in different years and from different sources. The collection process includes all the three possible techniques we have presented previously, i.e. the phone, home and master legal collection.

Our sample comprehends data on 5210 positions owned by the company (categorized as Own credits). All positions are unsecured credits to retail customers. The securities were acquired from 13 original owners. Some securities from the same originator were acquired in different moments.

The sample originally contains general personal data of debtors, together with the ones concerning the credit. Specifically, the following variables are present in the sample:

- Date of birth;
- Gender;
- Province of birth;
- Region of birth;
- Province of residency;
- Region of residency;
- Original owner of the credit;
- Type of credit;
- Year of acquisition of the credit;
- Total to recover (Capital + Interests);
- Total Recovered;
- Amount paid to the agent;
- Closed positions (in the form of true or false);
- Year of closing of the position;

There is absence of data for specific cases. Specifically, only part of the credits has been recovered, while some positions are still under management. In the cases where dossiers are open, no year of closing is presented.

### a. Descriptive Analysis of the Sample

We offer a general analysis of each variable in order to have a better understanding of the composition of the portfolio.

| | Age | Age (Underwriting) |
|---|---|---|
| Mean | 57.77 | 40.69 |
| Std | 12.31 | 12.01 |
| Min | 33.02 | 17.03 |
| 25% | 48.60 | 31.74 |
| 50% | 55.99 | 38.93 |
| 75% | 65.48 | 48.20 |
| Max | 109.87 | 89.53 |

*Table 4 Descriptive analysis of the "Age" and "Age at underwriting" (estimated). Source: own data.*

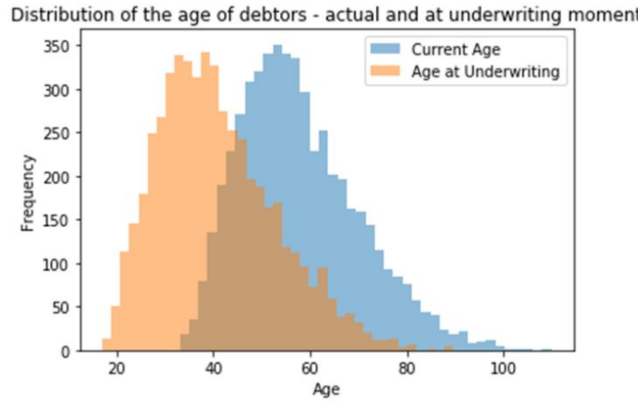



*Figure 12 Distribution of the parameters "Age" and "Age at underwriting" (estimated). Source: own data.*

**Age**: the expected age derives from the birth date of each debtor. It is expected since some debtors can be deceased. The results are summarized in *Table 4.* The average actual age of debtors at June 2018 is equal to 57.77.

We can estimate the age of each debtor at the moment of the underwriting of the contract by taking into account the year of selling and subtracting to it an average of two years to each debtor, as suggested by the CEO of Teseo Srl. This is used as an estimation for the age of the debtors when credits were issued. By doing so, we obtain the results on the third column of *Table 4*.

Both parameters follow a distribution as described in *Figure 12*. The distribution of the actual age has its highest frequency at its average and is positively skewed. We find the same skewedness for the age at underwriting, but here the highest frequency is found at around 35. For both parameters, Pearson's measure for skewedness, computed taking into account the median, is positive and equal to 0.43. The excess kurtosis is equal to 0.20 and 0.12 respectively for the actual age and the age at the underwriting moment. The two parameters describe a distribution similar to the normal distribution.

**Type of the credit and original owner of the credit**: the sample presents information about the original owners of the credit. They are 13, evenly distributed in the quantity acquired by each originator. Some of the credits were acquired by the same originator in different years. This data

| | Quantity | In % |
|---|---|---|
| A | 3,818 | 73.28% |
| CC | 218 | 4.18% |
| B | 1,174 | 22.53% |

*Table 5 Type of Credits. Source: own data.*

has been summarized distinguishing three main type of credits, i.e. credit for car acquisition (described as "A"), general financial or consumer credits ("CC") and banking credits ("B"). The distribution of our sample among these three is summarized in *Table 5*.

**Year of acquisition**: the credits of our portfolio were acquired in different years. The first year of

| Year | Quantity |
|---|---|
| < 2000 | 161 |
| 2000 | 599 |
| 2001 | 264 |
| 2002 | 670 |
| 2003 | 296 |
| 2004 | 721 |
| 2005 | 1090 |
| 2006 | 1045 |
| 2007 | 227 |
| 2008 | 0 |
| 2009 | 0 |
| >= 2010 | 136 |

*Table 6. Year of Acquisition. Source: own data.*

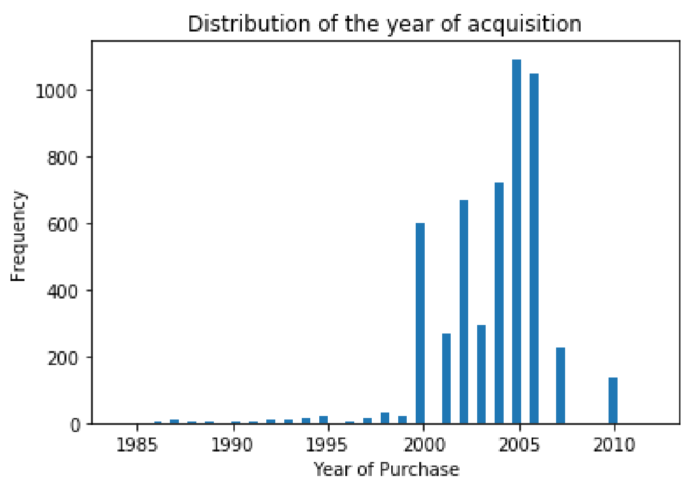


*Figure 13. Distribution of the year of acquisition of credit securities. Source: own data.*

acquisition is 1984 while the last is 2012. As presented in *Table 6* and *Figure 13*, the main purchases happened at the years 2000, 2002, 2004, 2005 and 2006.

**Total to recover:** the total to recover is made up by the sum of the unpaid capital plus the unpaid interests and penalties for the delay in the payments. In our sample, interests and delinquency sums are not separated variables, but we can see a correlation between the year of purchase and the amount of interest over the capital (calculated as interest / capital). Specifically, the correlation index for the two variables is equal to -0.24. This means that, as time passes by, the impact of interest on the total amount to be repaid increases due to the double effect of increasing interests and delinquency penalties.

| | Total to recover | Capital | Interest | Interest over capital | Interest over Total |
|---|---|---|---|---|---|
| **Mean** | 11,920.08 € | 7,741.10 € | 4,178.99 € | 0.591 | 0.352 |
| **Std** | 11,182.62 € | 7,978.80 € | 3,750.42 € | 0.311 | 0.105 |
| **Min** | 147.11 € | 124.13 € | - € | 0.000 | 0.000 |
| **25%** | 4,591.92 € | 2,917.05 € | 1,450.46 € | 0.410 | 0.291 |
| **50%** | 9,245.16 € | 5,807.19 € | 3,151.11 € | 0.500 | 0.335 |
| **75%** | 16,239.93 € | 10,304.80 € | 5,973.92 € | 0.730 | 0.421 |
| **Max** | 226,429.61 € | 171,461.38 € | 54,968.23 € | 2.550 | 0.719 |

*Table 7 Total to recover, capital and interest. Source: own data.*

For what concerns capital, its average is equal to € 7,741.10 (*Table 7*). The sample contains some outliers since 75% of the number of credits have a capital value lower than € 10,304.80, while its maximum value is in the order of the hundreds of thousands. In particular, only seventy positions have the value of the capital parameter higher than €30,000 and nineteen a value higher than €50,000.

The distribution of the unpaid capital amount is the one shown in *Figure 15*. More than half of the total number of credits have a capital value lower than €6,000. The ranges with a higher frequency

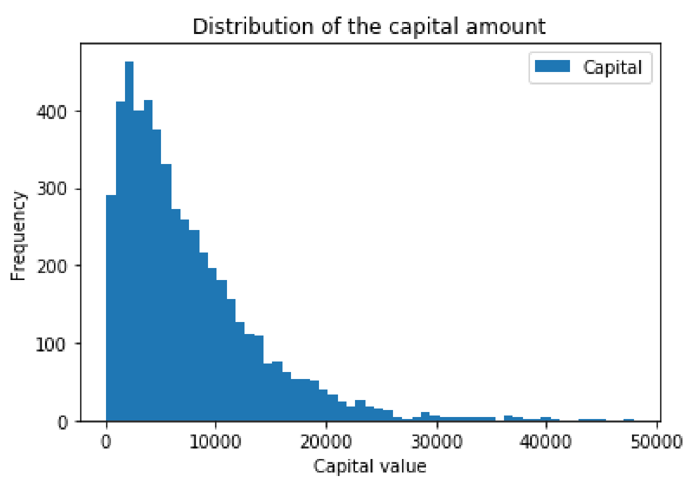



*Figure 14. Distribution of the capital amount. Values higher than € 50 k has been taking out of the graph. Source: own data.*

are the ones between €1,000 and €2,000 and between €2,000 and €3,000, for a total of 501 and 526 units respectively.

Pearson's parameter for skewedness, computed considering the median of the distribution, is equal to 0.73. The value confirms the existence of a tail on the right side of the distribution and highlights the presence of outliers. These characteristics are remarked by the value of the excess kurtosis[6] of 87.573, indicating a leptokurtic distribution.

It is importance to notice that the values of the capital amounts contained in our sample are not necessarily the initial amount of the credit issued by the original lender. In fact, most of the credit securities were sold after some initial repayments; the security came to be a past-due credit subsequently.

For the interest parameter, observations are centered in the range between €1,000 and €2,000

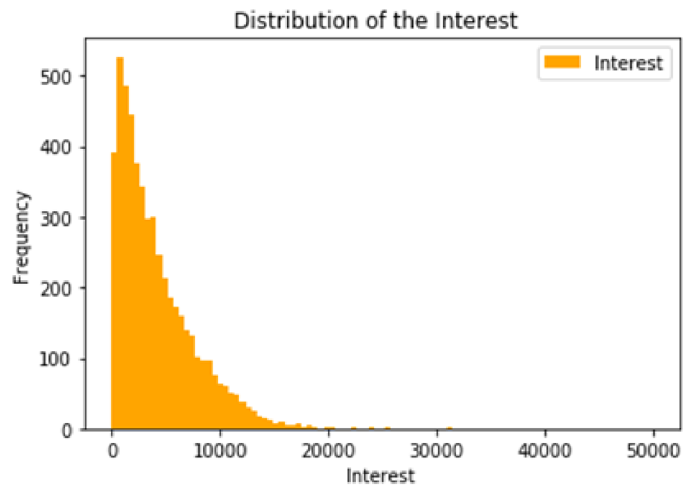



*Figure 15. Distribution of the interest amount. The scale and limits of the axis are the same as for the capital distribution to allow of comparability. Source: own data.*

(*Figure 16*). Half of the values are lower than €3,151.11 (*Table 7*).

The values are highly concentrated in this first range, but the distribution is positively skewed with a Pearson's parameter of 0.822, representing the existence of a tail on the right side of the distribution. The fact that the coefficient is lower than 1 confirms that values are not relatively far from the central values. Furthermore, there are less variability and outliers if compared to the distribution of the capital, as confirmed by an excess kurtosis of 17.174.

[6] The excess kurtosis is calculated as kurtosis minus 3, in order to have a direct comparison to the normal distribution.

Even if the maximum value is equal to €54,968.23, there are only 39 values higher than €16,000.

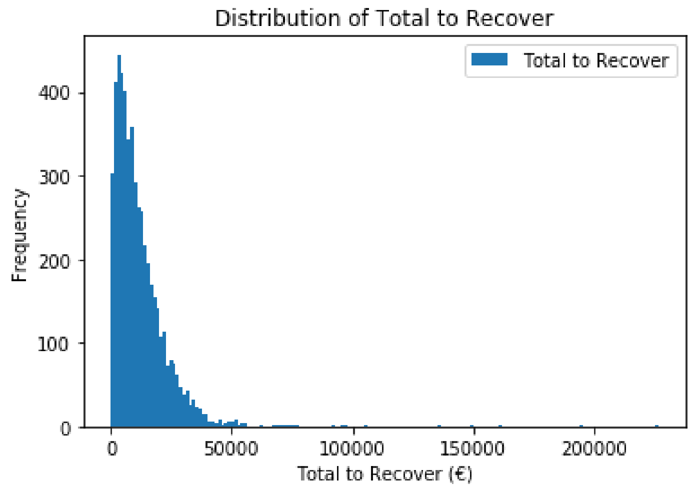



*Figure 16. Distribution of the total amount to recover. Source: own data.*

A lower variability of the interest is confirmed if we compare it to the capital parameter. The coefficient of variation[7] is, in fact, equal to 0.897 for the interest versus a value of 1.03 for the capital. The total amount to recover is the result of the two previous parameters (*Table 7*). Its mean is equal to €11,920.08 while the coefficient of variation corresponds to 0.938. The Pearson's

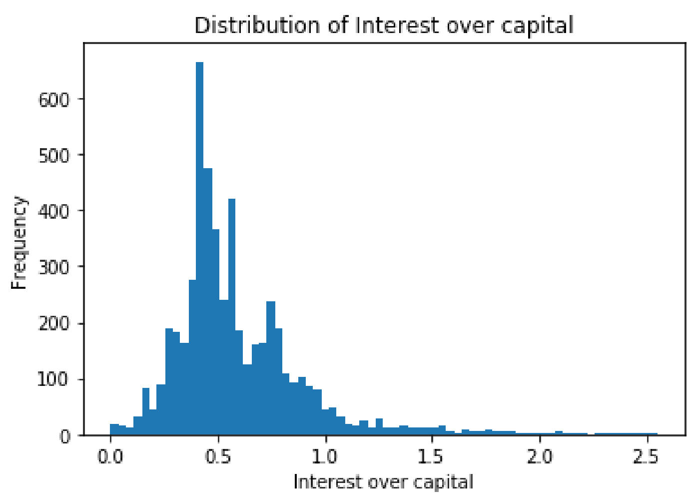



*Figure 17. Distribution of the interest over capital ratio. Source: own data.*

coefficient for skewedness is 0.718 indicating values concentrated in the center of the distribution. More than 50% of the value, in fact, are lower than €10,000.

[7] Coefficient of variation calculated as CF = Standard deviation / Mean

Finally, the excess kurtosis index confirms a leptokurtic distribution with many outliers (*Figure 17*), showing a value of 57.483.

We can see in detail the impact of interests over capital. On average, the interest corresponds to 59,1% of the capital (*Table 7*) with a maximum peak of 255%. For some positions no interest is presented. This is due to the solution of the litigation with a "partial final settlement" (*saldo e stralcio* in Italian), where the recovery agency writes off the interest over the credit to receive a lump sum payment equal to the capital. In these cases (8 totally), the operator of the agency decided to delete the interest on the dossier, even if this is not the main practice adopted by the company (in fact, most of the credits recovered with the "partial and final settlement" formula keep the interest recorded).

Even if the distribution shows a positive skewedness as for the precedent parameters, the variability of the interest on capital ratio is lower as demonstrated by the value of the kurtosis, equal to 6.732. A higher concentration of data is shown also through the coefficient of variation equal to 0.527.

**Closed positions and total recovered:** the number of closed dossiers is equal to 2740 (52,59% of the total) of which 594 (21.68% of closed positions) had only a partial recover, 159 units (5.8%)

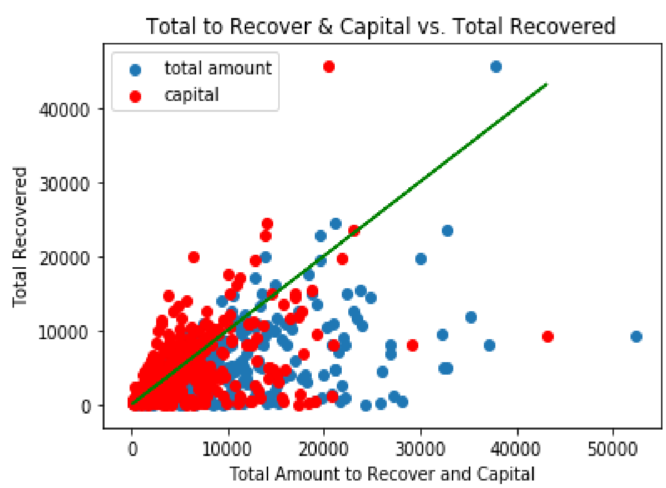



*Figure 18. Credits partially and fully recovered. Source: own data.*

had at least the capital amount recovered, but not the full amount, while 85 had the whole position recovered (3,10% of the total). The total amount recovered for closed positions is equal to € 2,794,045.82 over a total of € 29,622,420.52, of which € 19,687,362.25 represents the capital amount. The total amount recovered is equal to 9.43% of the total sum to recover and 14.19% of the capital. *Figure 18* captures the portion of the recovered amount compared to the capital and to the sum of capital plus interests. Red points on the left of the 45° line represent credits that have been recovered at least for the capital amount, while blue dots represent the ones fully recovered. All dots to the right and below the line are credits only partially recovered.

As stated before, the year when positions have been closed are not available for all dossiers. Considering the available data, the first positions on the portfolio were closed during the year 2008. Most dossiers were closed during 2016. The portfolio is still under work by the credit recovery agency.

**Incentive to agent:** during the phase of the home collection, agents are entrusted to physically meet the debtor and eventually collect the payment of the credit. Agents receive a double incentive

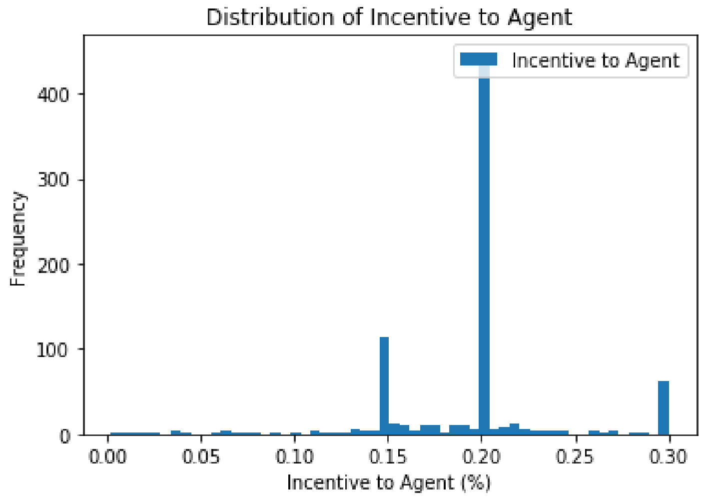



*Figure 19. Distribution of Incentive to Agent. Source: own data.*

through a fixed payment per visit plus a variable payment in the form of a percentage on the total recovered. Furthermore, agents have different contracts and the percentage of their commission, as well as the fixed amount per visit they receive, may vary.

We can identify three main commissions percentage: 0.15, 0.2 and 0.3 of the amounts recovered.

Apart from this, agents may receive a fixed amount per visit. Looking at the data, this sum goes from € 0 for some agents, up to € 80 for some others. The fixed payment per visit varies not only from agent to agent, but also according the distance agents cover to reach the debtor (*Figure 19*).

**Gender:** our sample presents a lower number of females than males (*Table 8)*. Females are 1371 on the total of 5210 (26,31%) versus 3839 males (73,69%).

There is no obvious difference between the two categories for what concerns the age. The main differences concern the average capital lent and the corresponding interest, for a similar relative magnitude (females have a -7.04% of the male amount, on average, while the interest over the capital ratio is the same for both genders).

The gap between genders is evident in the performance: females tend to meet more often their obligation both in terms of units collected (19.26% of number of credits collected over the total owed versus a performance of 15.86% for males) and of the amount paid (on average women pay 17.45% more than men, even if they start with a lower amount they owe).

| Gender | # Units | Avg Age | Avg Capital | Avg. Interest | Avg. Int. Capital | Avg Rec. Sum | % Rec. Sum | # Collected | % Recovered |
|---|---|---|---|---|---|---|---|---|---|
| Female | 1371 | 57.456 | € 7,359.23 | € 3,989.25 | 0.591 | 631.56 € | 8.58% | 264 | 19.26% |
| Male | 3839 | 57.880 | € 7,877.47 | € 4,246.74 | 0.590 | 521.37 € | 6.62% | 609 | 15.86% |
| **Total** | **5210** | **57.768** | **€ 7,741.10** | **€ 4,178.99** | **0.591** | **550.37 €** | **7.21%** | **873** | **16.89%** |

*Table 8. Comparison of the main variable between males and females. Source: own data.*

**Geographical distribution:** the sample description with regards to the region of residency is summarized in *Table 9*. As for UNIREC's report (UNIREC, 2019), the regions with a higher number of past due credits are Lombardy, Lazio and Sicily. There is little difference with regards to the age of debtor, even if in Sicily and Molise the age is higher with regards to the average of 57.77 (63.82 and 59.7).

The amount of capital to be repaid displays peaks in both southern (Sicily, Apulia, Basilicata) and northern regions (Veneto, Lombardia), while the interest over capital is well distributed along the whole peninsula except from a peak in Umbria and Molise, that, on the other hand, account for a lower number on the total units of credits. As for UNIREC's analysis, northern and alpine regions (Liguria, Veneto, Friuli, Piedmont and Lombardy) show a better performance, in terms of the sum of the total amount recovered divided by the sum of the total capital, than southern regions and islands (Molise, Campania, Sicily and Apulia). Considering the amount recovered, the performance goes from a higher 10.63% (Liguria) to a lower 2.47% (Abroad), ignoring the 0% of Molise.

| Region of Residency | N° Credits | Avg. Age | Avg. Capital | Int/Capital | Avg. Tot Rec. | % Capital | N° Recovered | % on Total | UNIREC |
|---|---|---|---|---|---|---|---|---|---|
| Lombardia | 844 | 56.32 | € 7,844.95 | 0.59 | € 721.95 | 9.20% | 187 | 22.16% | 12.0% |
| Sicily | 630 | 63.82 | € 8,699.19 | 0.58 | € 374.57 | 4.31% | 80 | 12.70% | 9.0% |
| Lazio | 545 | 57.35 | € 7,564.81 | 0.60 | € 486.34 | 6.43% | 89 | 16.33% | 12.0% |
| Veneto | 397 | 58.81 | € 8,339.80 | 0.55 | € 883.78 | 10.60% | 101 | 25.44% | 7.0% |
| Emilia Romagna | 377 | 55.46 | € 7,056.11 | 0.59 | € 569.56 | 8.07% | 75 | 19.89% | 8.0% |
| Campania | 372 | 56.89 | € 7,323.77 | 0.58 | € 279.39 | 3.81% | 31 | 8.33% | 10.0% |
| Tuscany | 371 | 56.39 | € 7,401.43 | 0.61 | € 626.27 | 8.46% | 64 | 17.25% | 8.0% |
| Piedmont | 301 | 56.97 | € 7,452.20 | 0.61 | € 697.41 | 9.36% | 56 | 18.60% | 9.0% |
| Apulia | 288 | 57.68 | € 8,440.59 | 0.57 | € 367.21 | 4.35% | 32 | 11.11% | 9.0% |
| Calabria | 275 | 55.31 | € 8,033.64 | 0.64 | € 369.82 | 4.60% | 24 | 8.73% | 8.0% |
| Friuli Venezia Giulia | 264 | 57.50 | € 7,431.87 | 0.55 | € 698.60 | 9.40% | 45 | 17.05% | 13.0% |
| Sardinia | 124 | 58.74 | € 5,743.92 | 0.64 | € 420.39 | 7.32% | 16 | 12.90% | 11.0% |
| Trentino Alto Adige | 90 | 57.75 | € 7,479.38 | 0.58 | € 276.98 | 3.70% | 14 | 15.56% | 7.0% |
| Liguria | 81 | 59.43 | € 6,875.88 | 0.64 | € 730.68 | 10.63% | 15 | 18.52% | 8.0% |
| Marche | 72 | 56.21 | € 7,312.59 | 0.60 | € 477.15 | 6.53% | 12 | 16.67% | 6.0% |
| Abruzzo | 63 | 55.87 | € 7,448.34 | 0.61 | € 355.28 | 4.77% | 9 | 14.29% | 7.0% |
| Umbria | 52 | 58.58 | € 7,407.98 | 0.71 | € 595.59 | 8.04% | 11 | 21.15% | 7.0% |
| Basilicata | 25 | 58.63 | € 8,430.78 | 0.52 | € 812.43 | 9.64% | 6 | 24.00% | 10.0% |
| Valle d'Aosta | 11 | 53.83 | € 7,038.64 | 0.55 | € 460.53 | 6.54% | 4 | 36.36% | 12.0% |
| Molise | 6 | 59.70 | € 5,441.50 | 0.71 | € - | 0.00% | 0 | 0.00% | 15.0% |
| Abroad | 22 | 51.92 | € 7,826.63 | 0.52 | € 192.96 | 2.47% | 2 | 9.09% | 5.0% |

*Table 9. Geographical distribution. All values are averages and UNIREC performance is calculated with regards to the amount recovered vs. amount entrusted. The table shows (from the left): the number of credits per region, the average age of the debtor, average capital amount, the ratio of the interest over the capital, the average amount recovered, the ratio between the recovered amount over the capital, the number of at least partially recovered dossiers and the number of recovered dossiers over the total number of dossiers per region. Source: own data and UNIREC IX annual report (2019).*

These results confirm a direct correlation between the per capita available income in different regions and the performance. It is important to notice some exceptions, as for the northern region Trentino Alto Adige, that shows a weak performance, and Basilicata, with a higher recovery rate while being a southern region.

Notice that some regions have few data which can lead to biased estimates, as for the Molise case. Furthermore, Teseo has a higher presence of agents in specific regions, which can lead to a better performance for these regions. But generally, the breakdown of the performance for the different Italian regions of the sample reflects the results presented by UNIREC (Centro Studi UNIREC, 2019).

Finally, to allow for a comparison with the results collected by the association of credit collection agencies, the geographical performance reported by UNIREC for 3$^{rd}$-party credits is displayed on the last column of the table, and it is calculated as the amount collected over the total amount entrusted for each region. As described in the table, the higher divergences between our sample and UNIREC's results regards Campania, Lazio and Valle D'Aosta.

# 7. Model

The aim of this work is to estimate the price of a securitization made of past due, unsecured credits issued to retail clients. The credits in our sample are secondhand repurchased credits. The sample that is used to run the model is made of credits purchased by Teseo S.r.l. in different years and from different sellers.

The pricing of secondhand past due loans is a difficult process, especially for small and medium credit recovery agencies operating in the factoring sector. The main difficulty related to the estimate is the fact that these credits have often changed ownership more than once, losing data at each transaction. The available information for the final acquirer is usually limited to basic data about the debtor and the credit itself, such as the capital lent and the interests. All further information, such as the last verified residency of the debtor, the frequency of the previous payments or the debtor's credit score are often lost.

It is useful then, especially for SME credit recovery agencies, to rely on quantitative methods to better evaluate a credit at the moment of the acquisition. Moreover, the influence of each variable described by the model can help determine the main factors that affect the performance of the agencies.

In the model, the price of a defaulted security is obtainable with the discounted cash flow model. The inputs of the model are:

- Expected recovery rate;
- Costs;
- Discount rate;
- Timing of the recovery.

## a. The Expected Recovery Rate

The recovery rate is defined as the proportion of money that financial institutions or credit recovery agencies are able to collect in terms of the outstanding balance at default. The recovery rate is defined as:

$$Recovery\ Rate_i = \frac{\sum Net\ Collections_{i,t}}{Outstanding\ Balance\ at\ Default_i} = \frac{Total\ Recovered_i}{Total\ to\ Recover_i}$$

This usual definition of the recovery rate is a common parameter used in the calculation of the expected loss (Loss Given Default, or LGD) or regulatory capital under Basel II for a banking institution. In our model, the credits are not recovered by their original owner. They are indeed purchased credits, such that there is no LGD for the acquirer of the credit.

During the collection process, agencies aim to recover the full amount made of the capital plus interests and penalties. But in the frequent case where the debtor has a problematic financial situation, agencies focus on recovering at least the capital amount. Furthermore, the capital amount is the usual recovery target for the final settlement solution (*Saldo e Stralcio* in Italian). Considering this, in this sample, the dependent variable “recovery rate” is defined as:

$$Recovery\ Rate_i = \frac{\sum Collections_{i,t} - \sum Cost_{i,t}}{Unrecovered\ Capital_i} = \frac{Total\ Recovered_i}{Unrecovered\ Capital_i}$$

In this model, the costs linked to the collections are considered separately since the collected data report the administrative costs only for some securities. This, on the other hand, allows to estimate their impact on the recovery rate, but not to analyze the connected expenses for each security.

At an operational level, recovery agencies and financial entities have different options for the recovery (*Figure 20*). The optimal scenario is the one where the credit is fully recovered, both in the nominal value plus the interests. This result is usually achieved with the so-called *piano di rientro* in Italian, i.e. the installment plan, a series of regular payments for a previously agreed number of periods. Rarely the debtor reimburses both the interests and the nominal value in a lump sum payment.

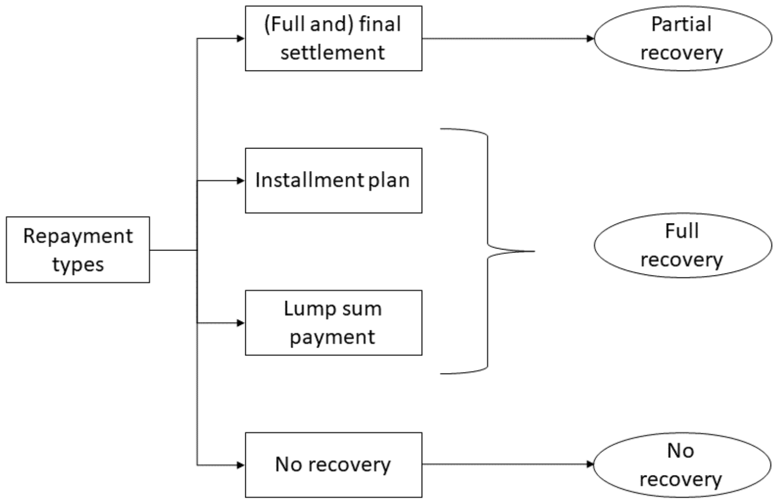



*Figure 20. Different recovery solutions. Source: own elaboration*

Another possibility is the one where the debtor does not repay any amount of the credit, but the agency faces costs. The dossier has then only outflows. For these situations, in our sample, the recovery rate will be set to zero since costs are considered separately, even if it is a negative recovery rate.

The recovery rate can also be higher than one, in case the owner of the credit is able to recover also the penalties connected to the past due position and, in our case, the interests. The sample used to this analysis contain positions that have a recovery rate higher than 1. Such a recovery rate is common in cases of a low amount to recover versus a high penalty sum.

The recovery ratio is then a ratio that usually lies between zero and one, although lower or higher values are possible. In the present sample, there are no negative ratios, while credits where the recovery rate is equal or higher than 3 are treated as outliers when estimating the recovery rate through an OLS regression and are not used to compute the model. The distribution of the recovery rate is presented in *Figure 21*.

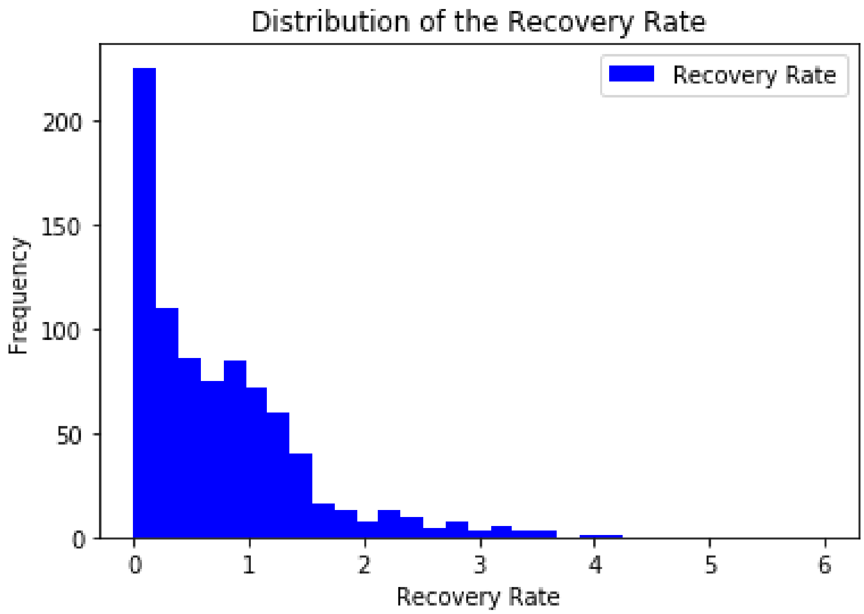



*Figure 21. Distribution of the recovery rate. Source: own elaboration from the dataset.*

As we can see from *Figure 2*, the peak of the distribution lies on the boundary value 0, meaning that most of at least partially recovered credits have a recovery rate close to zero. Notice that the histogram represents data of closed positions. The average recovery rate of the subset is 0.74 while the maximum value is 6.88, a case where the capital sum is small, such that the recovery of penalties and interests lead to an incredibly high recovery rate. The median recovery rate is 0.57, confirming a high concentration of recovery rates on values closer to zero and a right-skewed distribution.

The sample used to compute this model contains only credits recovered through the non-judicial recovery process. Furthermore, only extraordinary administrative costs are embedded in the dataset and they are not reported for all securities. Considering this aspect of the dataset, to estimate the associated expenses connected to the recovery of the securities, costs items for all securities are estimated from the dossiers where they are displayed.

### b. Review of Existing Models

The recovery ratio of our model is estimated by a mixed logistic regression and OLS model. The logistic model is utilized to estimate the probability to recover any amount of the credit. The multiple OLS regression is then used to calculate what is the expected recovery rate.

The goal of the model is to get an estimate of the expected cash inflows. Together with the OLS estimation, a beta regression and a Lasso regression, inspired by the model of Hui Ye & Anthony Bellotti (Hui Ye, Anthony Bellotti, 2019), were used. But they showed to underperform with regards to the mixed logistic-OLS regression and are not included on this dissertation.

The OLS, the LASSO regression and the logistic regression were performed with the Python libraries *statsmodel* and *scikitlearn*. The beta regression was performed with the package *betareg* of R. While the LASSO model just caught the influence of few variables, the beta regression was able to explain only 32% of the recovery rate of our test dataset.

The main challenge in estimating the recovery rate for unsecured, second-hand credits to retail customers is the absence of detailed information about the debtor. In particular, data from the past recovery activity of the seller of the credit is not transmitted to the buyer of the securities. This phenomenon is more significant in case the credit was issued a long time before its last purchase. In these situations, information about the debtor's residency and contact number tend to be unreliable, making the recovery process riskier and more expensive.

Another bottleneck in estimating the recovery rate is connected to the bimodal property of recovery rates distribution, that have high concentration in the boundary points 0 and 1, meaning that people usually either repay in full or repay nothing of their debt. Furthermore, the recovery rate is often truncated in the interval [0;1] when dealing with models estimating the loss-given-default (LGD) (Bellotti and Ye, 2019).

Even though there were previous studies trying to catch this element, our distribution showed many cases of partial recovery (which means that the recovery rate was between 0 and 1), due to the final settlement formula, that leads to partial repayment of the owed amount. Furthermore, recovery agencies and their clients may target to recover at least the nominal capital amount of the security, reducing the bimodality of the model.

Previous models that tried to estimate the recovery rate for past due credits are the ones of Bellotti and Crook (2012), Calabrese (2012), Qi and Zao (2011), Loterman et al. (2012) and Bellotti and Ye (2019).

Bellotti and Crook built a Tobit and decision tree models along with beta and fractional logit transformation based on a dataset of 55,000 defaulted credit cards in UK between 1999 and 2005.

The conclusion of their model was that OLS regression with macroeconomic variables was the better performing estimator (Bellotti and Crook, 2012).

Calabrese's estimate proposed a model where boundary values of 0 and 1 are modelled as Bernoulli random variables while the continuous between the two limits is modelled by a beta regression. This model was then tested by computing the recovery rate of loans issued by Bank of Italy from 1985 and 1999.

Qui and Zao (2011) applied four linear models and two non-linear models (regression tree and neural network) to model the LGD of 3751 defaulted bank loans from the United States issued between 1985 to 2008. The result was that the OLS was one of the best performers.

Loterman (Loterman et al., 2012) performed a benchmark study by comparing twenty-four different model. The conclusion of Loterman is that non-linear models, such as neural networks, support vector machine and mixture models perform better than linear models. But among linear models, ordinary least square tends to perform better than others.

Finally, Bellotti and Ye showed that a mixed model made of a logistic regression for boundary values and a beta regression for the continuous values between 0 and 1 performed better than a Lasso regression or the OLS. The model was able to explain about 69% of the variation in the recovery rate, due to the richness of data, especially of collection information such as the number of calls, the credit bureau scores or the total number of physical and telephone contacts with the debtor (Bellotti & Ye, 2019).

Until now, for what we know, no previous attempts to specifically model the recovery rate for second-hand unsecured credits to retail clients was find. All analyzed models treat mostly first-hand defaulted credits with a financial or banking origin. Credits tend to be secured and issued to both individuals and corporate entities. The proposed mixture logit-OLS model aims to estimate the recovery rate of second-hand credits to retail, that are unsecured and of both a financial and consumer type. The credits are sold through factoring operations as a basket of securities.

### c. Logistic Regression

We estimate the probability of recovery with a logistic regression. The independent variables are:

- Age of the debtor, as of August 2019 (*Age*);
- Gender of the debtor, that assigns a probability of recovery if the debtor is a woman (*Gender_F*). The case where the debtor is a man has shown to be irrelevant, i.e. it yields a coefficient equal to zero;
- If the debtor changed its residency (*Moved*). The variable is obtained by inserting a value equal to zero if the province of residency is equal to the province of birth or one if the two provinces are different;
- Year of selling, that describes the year of purchase of the security. It is split in 5 ranges that are useful to reduce the impact of outliers (*Y_S_Bin*). The composition of the different bins is described in *Table 10*. Notice that binning a variable consist in a way to group a number of values into a smaller number of "bins". For example, if you have data about a group of students, you may arrange their grades into a smaller number of intervals, such as insufficient results (0 to 6), sufficient results (6-7), good results (7-9) and optimal results (9-10);
- Capital Bin, a variable that divides the capital amount in 5 different ranges. The reason why the capital is translated into bins is to remove outliers and to capture the effect of different magnitude classes of the capital on the probability of recovery (*Capital_Bin*). The formation of the bins is described in *Table 11*;
- Type of credit, i.e. if the credit is a consumer credit (*Type_CC*), a consumer credit having as underlying the purchase of a car (*Type_A*) or a banking credit (*Type_B*);
- The ratio of the interest over the total capital, a variable that captures the impact of the interest on the -total amount lent (*Interest over capital*). Notice that the interests in our sample comprehend also penalties. Hence, for securities where the lent value is low, the impact of the interests and penalties tend to be higher, yielding a high interest over capital ratio, but the low amount of capital to repay makes it more likely for the debtor to fulfil the obligation;
- The residency of the debtor, where a location is included only when it offers a significative result for the regression (*Residency*).

| Capital | Capital_Bin | Quantity |
|---|---|---|
| *0-2,030* | 1 | 167 |
| *2,031-3600* | 2 | 167 |
| *3601 - 5650* | 3 | 167 |
| *5651 - 9000* | 4 | 168 |
| *9001 +* | 5 | 168 |

*Table 10. Capital Bins. Source: own data.*

| Years | Y_S_Bin | Quantity |
|---|---|---|
| 2002-1985 | 1 | 1338 |
| 2004-2003 | 2 | 781 |
| 2005 | 3 | 736 |
| 2006 | 4 | 533 |
| 2012-2007 | 5 | 189 |

*Table 11. Year of Selling Bins. Source: own data.*

## 1. Results

The detailed results of the model are shown on *Annex 1* together with the stacked bar graphs showing the relationship between the variable and the likeliness of the recovery.

The model offers the following results, estimating the probability of the recovery as:

$$P\_recovery = -0.025 * Age + \beta\_1 * Gender - 0.56 * Moved + 0.42 * Y\_(S\_Bin) - 0.05 * Capital\_Bin + 1.07 * Interest\ Over\ Capital + \beta\_2 * Type + \beta\_3 * Residency$$

Where the estimated coefficients are:

$\beta\_1$ is equal to +0.25 in case the debtor is a woman, 0 if the debtor is a man;

$\beta\_2$ is equal to +0.26 if the credit was originally issued to purchase a car, -0.15 if it has a financial nature while it has no effect on the probability of recovery in case it is a generic consumer credit.

$\beta\_3$ is equal to -0.43 if the actual residence of the debtor is in the south of the Peninsula, +0.02 if the debtor is resident in central regions, +0.32 for northern inhabitants and -2.47 for debtors living abroad.

As we can see from the table on Annex A, all variables are significant, even if the residency in central Italy tends to be less reliable. The decision to include this variable is to offer a wider view regarding the effect of the debtor's geographical location on the likeliness of the recovery.

The results highlight important elements.

A first point is that the older the debtor, the more unlikely is the recovery. This effect of the debtor's age on the probability of recovery may be indirectly due to the aging of the credit itself: old credits, as the ones in our sample that were purchased in 1986, will systematically belong to older debtors. Older credits tend to perform worst then new acquired securities.

The correlation between the time passed from the moment that the credit became a past due position and its probability of recovery is confirmed by the results for the year of selling (*Y_S_Bin*). The higher the bin of the year of selling, i.e. the more recent is the year of purchase, the more probable is the recovery. The results confirm what reported by UNIREC in its annual report on the activity of credit recovery agencies (UNIREC, 2019).

For what concerns the gender of the debtor, if the debtor is a woman the debt more likely to be recovered. This confirms what already spotted in the descriptive analysis of the sample. On the other hand, the fact that the debtor is a man does not indicate a higher or lower likeliness of recovery.

Considering the specifics of the credit, the model tells that the higher is the capital amount, the lower is the probability of recovery. The reason is straightforward: a higher amount of debt can dissuade the debtor to fulfil its obligation or can find the debtor without the resources to repay the amount owed. In fact, accepting to repay a high amount of debt is for the debtor a commitment to fixed monthly payments for a long period of time.

On the other hand, if the capital to be repaid is relatively small, the debtor is more likely to fulfil its obligation. In fact, the debtor, without facing high expenses, is able to ask for credit in the future, to enhance its credit score and to avoid other types of actions from the creditor.

A similar conclusion can be made considering the interest over capital ratio. A high ratio means that the debtor whether owes a low capital amount to the creditor or has a higher incentive to accept a solution such as the final settlement. In fact, in this type of settlement, all penalties and interests are not paid back creating the psychological effect of a high discount on the total sum owed.

With regards to the type of credit, it suggests that consumer credit and credit issued to car purchases tends to be repaid more frequently than financial credits, probably due to the effect of the presence of an underlying to the debt.

Finally, considering the geographical distribution linked to the likeliness of repayment, the results confirm the ones from the UNIREC report: regions with a more dynamic and prosperous economic environment makes it more likely for debtors to fulfil their past due obligations. Northern regions reflect a higher income per capita, and hence a higher disposable income that can be used to fulfil the debtor's obligation. Central regions display a more limited likeliness of repayment if compared to the north of the Peninsula. Considering the significance of the result, the parameter is likely to be effectively close to zero. Southern regions and islands (Sicily and Sardinia) are regions with a lower per capita income. Residents of these regions are less likely to fulfil their obligations.

Finally, previous residents in Italy that moved to other countries are unlikely to repay their debt. This may be due to the fact that they are not under the Italian jurisdiction anymore, and hence don't have any legal reason to meet their obligations.

The logistic regression offers the first elements to evaluate credit securities. In the process of the pricing of past due credits, the probability deriving from the logistic regression is used to estimate the expected total amount recovered for each security. The values computed using the previous equation that exceed the value of 1 is approximated to the boundary value of 1, as well as negative values are approximated to 0.

### d. The OLS Regression and Recovery Rate

Once the probability of recovery is obtained, it is important to estimate its magnitude. This input of the model is computed through a multiple OLS regression.

The variables used to estimate the recovery rate, i.e. the percentage of the recovered amount over the outstanding capital at default, are:

- If the debtor residency is different from its place of birth (*Moved*);
- The employment rate of the province where the debtor resides at the time of the closing of the dossier (*Employment_Y_C*). The data is taken from the ISTAT database. The choice of considering the province of residency instead of the region depends on to the fact that provinces are higher in number, allowing for a higher volatility of the variable. Notice that the employment rate is expressed as a value between 0 and 100, i.e. as a percentage multiplied by 100, as proposed on the original ISTAT dataset.;

- The ratio of the interest on the capital amount (*Interest over Capital*), which tells the impact of the interest on the unpaid capital amount;
- Number of payments, obtained from the dataset "Movements". The variable indicates in how many tranches the debtor has repaid its debt (*N payments*);
- Gender of the debtor (*Gender*);
- Capital bin (*Capital_Bin*). The formation of the bins is described on the *Table 10*;
- Type of credit. The credit can be a consumer credit (*Type_CC*), consumer credit for a car purchase (*Type_A*) or a financial lending (*Type_B*);
- The region of birth (*Birth_Region*). The dataset contains also data about the residency of the debtor, which is the variable used for the logistic regression. Since for many debtors the region of residency and the one of birth are the same, the variable *Moved* was added and the region of residency was not taken into account in order to avoid multicollinearity. Notice that not all Italian regions are present in the sample. More specifically, no debtor in the dataset is born in Molise. Foreign macro regions of birth that are indeed in the sample are: Africa, America, Asia, eastern Europe (especially the Balkans and Rumania) and the central and western Europe.
- Year of closing of the dossiers. This variable tries to capture the economic conditions at the year of closing. Also, it substitutes another variable obtained from ISTAT describing the employment rate in the specific region for the year of closing, removed due to a high associated VIF factor. The variable is changed to five bins, i.e. ranges, to remove outliers, as displayed in *Table 12* (*Y_C_Bin*).

| Years | Y_C_Bin | Quantity |
|---|---|---|
| *1986-2002* | 1 | 224 |
| *2003-2004* | 2 | 175 |
| *2005* | 3 | 165 |
| *2006* | 4 | 198 |
| *2007-2015* | 5 | 76 |

*Table 12. Year in which dossiers are closed.*

## 1. Results

The results of the OLS regression are summarized in *Appendix B*, which includes also scatterplots graphs displaying the relation between the independent and different dependent variable.

The value of the R-squared is equal to 0.46 while the adjusted one is equal to 0.43, in line with the precision of the models reviewed in the previous paragraph.

The recovery rate is then modelled as:

$$RR_i = 0.11 - 0.031 * Moved_i + 0.25 * Employment\_Y\_C_i + 0.38 * Interest\ over\ Capital_i + 0.02 * N\ payments_i + \beta_1 * Gender_i + \beta_2 * Capital\ Bin_i + \beta_3 * Type_i + \beta_4 * Birth\ place_i + \beta_5 * Year\ of\ Closing_i$$

The specific value of the coefficient for the dummy variables are collected in the table of *Appendix B*.

The multicollinearity of the model is tested by computing the VIF[8] for each independent variable. As we can see, all variables have an acceptable level of VIF, lying generally below the threshold of 5, except for the employment rate at the year of closing, probably correlated with the bins of the year of closing. However it is included in the model due to its impact on the overall performance.

The eliminated dummies, which effect on the recovery rate is captured by the intercept, are:

- Male gender (*Gender_M*);
- The first capital bin (*C_Bin_1*);
- Type of financial credit (*Type_B*);
- Basilicata region of birth (*Birth_Basilicata*);
- First bin of year of closing (*Y_C_Bin_1*);

[8] The VIF, or Variance Inflation Factor, detects multicollinearity in a regression analysis. It is calculating by taking a regressor (i.e. an independent variable) and regressing it against all other regressors of the model. The R-squared values obtained from these regressions are used to calculate the VIF as:
$VIF_i = 1/(1\text{-}R\text{-}Squared_i)$. A VIF under 5 indicates that there is weak or absence of multicollinearity.

The model suggests a positive influence of the gender on the recovery rate if the debtor is a woman, confirming the evidence of the logistic regression not only on the probability of repay, but also on the overall amount given back.

Another factor that has a positive impact on the recovery rate is the employment rate of the region of residence of the debtor. The explanation is straightforward: a higher employment rate means a higher income per capita for the province, that leads to a higher recovery rate.

In case the debtor has moved from its original place of birth, the magnitude of the recovery tends to be lower, as described by the negative coefficient on the variable *Moved*.

A variable that has a positive influence on the recovery rate is the number of payments, suggesting that deferred payments lead to a better recovery rate, while lump sum payments are convenient in terms of the reduction of the risk, but it comes with a discount in terms of the amount recovered.

For what concerns the capital sum, the sample suggests that the higher the capital amount, the lower is the recovery rate. It is due to a double effect. On one hand, the disincentive for the debtor to commit to the payment of a large sum, often due to the difficulty to payback the owed amount. On the other hand, a higher capital amount allows the credit agency operators to allow for a greater discount in the form of final settlement plan, asking only for a fraction of the original capital amount.

This is partially confirmed by the paradox of a remarked positive influence (OLS coefficient equal to 0.38) of the interest over capital on the recovery rate, that follows the same argument presented for the positive effect of the variable on the probability of recovery. In essence, a high interest over capital ratio usually indicates a low capital amount, making the recovery more likely and the recovery rate (as the percentage over the capital amount), higher.

For what concerns the type of credit, it is important to notice that, while credits issued for the purchase of a car have a positive effect on the magnitude of recovery rate, those issued for general consumption have an opposite effect.

For what concerns the geographical area, no particular conclusion can be drawn. In fact, if the residency in northern and southern regions increases the probability of a recovery, the debtor's provenience from one of these regions impacts differently on the recovery rate, as shown by *Figure 22*. All betas are obtained through the OLS regression.

| | Region | Beta |
|---|---|---|
| North | *Veneto* | 0.017 |
| | *Trentino Alto Adige* | -0.038 |
| | *Lombardy* | -0.091 |
| | *Friuli Venezia Giulia* | -0.135 |
| | *Emilia Romagna* | -0.195 |
| | *Liguria* | 0.157 |
| | *Piedmont* | -0.031 |
| Center | *Abruzzo* | -0.172 |
| | *Lazio* | -0.129 |
| | *Marche* | -0.053 |
| | *Umbria* | -0.280 |
| | *Tuscany* | 0.157 |
| South | *Calabria* | -0.049 |
| | *Compania* | -0.105 |
| | *Apulia* | -0.123 |
| | *Sardinia* | -0.005 |
| | *Sicily* | 0.035 |
| Abroad | *Eastern Europe* | 0.045 |
| | *Europe* | 0.055 |
| | *America* | 0.229 |
| | *Africa* | -0.273 |
| | *Asia* | -0.594 |

*Figure 22. Region of Birth and impact on the recovery rate. The graph reports the coefficient of the linear regression obtained through the OLS regression for each region. Source: own data.*

Finally, for what concerns the year of closing, credits recovered before 2007 have a higher recovery rate, on average. After the financial crisis, from 2007 on, the impact of the year of closing on the recovery rate confirms a lower recovery rate, due probably to the financial crisis that hit the country. The higher recovery rate for credits recovered during the years 2005 and 2006 correspond to the years where the Italian GDP level was at its highest levels before the crisis, which is captured by the high coefficient of the variable.

Notice that we set boundary values for the recovery rate estimated with the equation resulting from the model. Specifically, the minimum value allowed is 0, while the maximum is of 3 for credits within the first and the second capital bin, and of 1.5 for all other credits.

The results of the logistic and the OLS regression together allow to calculate the expected cash inflows for each security. To complete the discounted cash flow model, we need to estimate the costs linked to the recovery, its timing and associated risk.

### e. Costs & Time of The Recovery

It is difficult to estimate the costs connected to the recovery of past due credits since the outflows vary depending on the business structure of the recovery. Considering this, the model allows the user to insert as input the average fixed expenses per dossier estimated by the operator. These expense item consist of the cost of human capital, administrative costs and other costs imputable to aspects of the operating organization.

In our model we estimate indeed the variable costs connected to the recovery process. Variable costs are usually connected to the capital to be recovered and refers to all the tools described in the previous chapters. Credit agencies usually uses more expensive services, such as the private investigation about the financial situation of the debtor, only when the capital amount is large enough to justify such cash outflow. Hence, the variable costs are estimated based on the capital bin the credit belongs to. The dataset used to estimate the costs is the movements dataset, which reports extraordinary costs as a variable. The results are described in *Table 13*.

| Capital Bin | Avg Extraord. Costs |
|---|---|
| 1 | 6,47 € |
| 2 | 12,41 € |
| 3 | 15,22 € |
| 4 | 17,05 € |
| 5 | 22,12 € |

*Table 13. Average Extraordinary expenses per capital bin of the dossier. Source: own data.*

Even if the costs may seem apparently low if compared to the capital bin, it is explained by the fact that from 4807 closed dossiers, only 166 had associated extraordinary costs.

Apart from the extraordinary costs and for fixed costs, the cost item that has the major impact on the overall revenue for the agency is the cost of the recovery agent. In fact, many credits are recovered physically by an agent entrusted by the company. In exchange for a successful recovery, agents receive a percentage of the recovered amount. This fraction tends to be a value between 10% and 20% of the recovered amount.

To estimate the cost of the agent we use the dataset 2, the one applied to estimate the recovery rate. According to the data, 799 credits out of 838 were recovered physically by an agent. Recovered credits belonging to the first capital bin had an average incentive to the agent equal to 18.72%. The percentage gradually decreases among the other bins, being 18.8% for the second bin, 18.63% for the third, 18.33% for the fourth and 17.77% for the last.

In the model, such cost is applied to the expected recovered amount in the form of a discount on each cash flow.

Summing up, credit recovery agencies face three main cost items:

- Fixed costs, connected to specific aspects of the business;
- Variable costs, linked to the credit itself and to its capital amount;
- Payments to the recovery agent, in the form of a percentage of the recovered amount.

In the model, the variable costs are subtracted from the first inflow, while the payment to the agent and fixed costs are discounted from each cash flow.

### f. Payment Timeframe

The timeframe associated to the repayment of open positions are estimated from the Movements dataset. In order to achieve a good estimate, we consider first the average number of payments for different capital bins, together with the average number of days between each payment. Credits are then clustered according to their capital bin, where each cluster will have its own recovery timing (*Table 14*).

| C_Bin | 1st Recovery | Average N° Days | Avg N° Payments |
|---|---|---|---|
| 1 | 4.2 | 57 | 9 |
| 2 | 3.8 | 46 | 13 |
| 3 | 4.4 | 48 | 15 |
| 4 | 4.3 | 71 | 14 |
| 5 | 4.9 | 43 | 16 |
| | **4.34** | **53.22** | **13.41** |

*Table 14. Timing of the recovery, reporting the years to the first recovery (1st Recovery), the average number of days between two payments (Average N° of Days) and the average number of payments (Avg N° Payments), for each capital bin. Source: own data, movements dataset.*

To obtain the estimates, the first step is to calculate the difference between the year of selling and the year of the first payment. This variable is expressed as *1$^{st}$ Recovery* in *Table 6* and describes the average number of years passed between the purchase of the credit and its first positive cash flow.

The number of payments is calculated as the average number of payments for each security within each capital bin (*Avg N° Payments*).

The average number of days between each payment is computed in a similar way and is described by the column *Average N° Days*. It is obtained by calculating the average number of days that passes between the payments of each security. The average number of days for each capital bin is then estimated as the mean of the average number of days of each security belonging to the specific capital bin.

The results of *Table 6* give important information about the recovery. The 5$^{th}$ capital bin usually is likely to be the hardest to recover, meaning that it takes more time to get a first payment from the debtor. Also, for the same bin the payments tend to be distributed in a longer timeframe. On the other hand, the fifth bin has a shortest period between two payments, that is higher for the fourth bin. The more efficient bin is the second, with the shortest waiting time between the acquisition and the first recovery, the second smallest number of days between each payment and the second smallest average number of payments.

It is important to notice that further clustering or a different approach can be used to better estimate the timeframe of the repayments, allowing to include also lumpsum ones. For the aim of the model, such approach can still offer a good performance and estimate.

### g. The Model at Work

Once all the inputs are obtained, it is possible to run the discounted cash flow model.

The first step is to consider the recovery rate, i.e. the expected amount that will be recovered as a ratio on the capital. If the recovery rate is multiplied for the capital amount, we obtain the expected total inflow.

Once the cash inflows are estimated, all costs have to be subtracted. The fixed, administrative costs are discounted from each cash flow. Also the percentage to the agent is subtracted for each payment. Since not every credit agency rely on agents on such a scale as shown in the model, the average ratio of 18% can be eventually changed, to reflect the specifics of the company.

Estimated extraordinary costs are discounted directly from the first income flow, since they usually materialize at the beginning of the recovery, when no reliable information about the residency or the phone number of the debtor is found. Notice that for those securities with the estimated recovery rate or the probability of recovery equal to 0, there will be no stream of negative cash flows. Only fixed and variable costs are considered for the first period.

Finally, cash flows are discounted at the three different discount rates of 12%, 9% and 15%, in order to offer a range of confidence for the price. The discount rate of 12% to 15% is indicated by professor Riccardo Tedeschi, senior specialist of Prometeia, a wealth management and financial advisor company, and professor at the University of Bologna (Riccardo Tedeschi, 2016). The reported discount rate is calculated on banking NPL. It is likely that the discount rate for unsecured credits issued to retail clients are slightly higher.

To clarify the functioning of the model, an example is reported. It calculates the price of a basket of 5 randomly chosen securities.

From the OLS and the logistic models codified in python, we obtain both the estimated recovery rate and the probability of the recovery for the five securities, as shown in *Table 15* (columns *Prob. Recovery* and *Predicted RR*). The table reports all necessary inputs of the discounted cash flow model.

| Capital_Bin | Capital | Est. N Payments | 1st Recovery | Average N° of Days | Predicted RR | Estimated Rec. Amount | Inflow i | Fixed Cost | Variable Cost | Incentive Agent | 1st Net CF | OtherNet CF | Prob. Recovery |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 13,106.81 € | 16 | 4.9 | 43 | **1.33** | 17,386.27 € | 1,086.64 € | 10 € | 22.12 | 17.77% | 861.43 € | 883.55 € | **66.4%** |
| 3 | 4,162.44 € | 15 | 4.4 | 48 | **1.11** | 4,619.31 € | 307.95 € | 10 € | 15.22 | 18.63% | 225.36 € | 240.58 € | **30.0%** |
| 2 | 3,593.74 € | 13 | 3.8 | 46 | **0.46** | 1,650.98 € | 127.00 € | 10 € | 15.41 | 18.80% | 77.71 € | 93.12 € | **81.6%** |
| 5 | 9,433.22 € | 16 | 4.9 | 43 | **0.57** | 5,393.20 € | 337.07 € | 10 € | 22.12 | 17.77% | 245.06 € | 267.18 € | **59.2%** |
| 5 | 12,256.93 € | 16 | 4.9 | 43 | **0.00** | - € | - € | 10 € | 22.12 | 17.77% | - 32.12 € | - € | **14.4%** |

*Table 15. Input data on 5 securities reporting: the capital amount, the estimated number of payments, the estimated years to the first recovery, the recovery rate predicted with the OLS regression. the estimated recovered amount, the gross cash flow, the costs, net cash flows and the probability of recovery predicted with the logistic regression. Source: own data*

The first step is to estimate the final recovered amount, corresponding to the column *Estimated Rec. Amount* on *Table 15*. The estimated amount that will be recovered is then divided by the number of payments, to obtain the inflows for each period (*Inflow i*).

The following step is to compute the expected first net cash flow and the following net cash flows (columns *1st Net CF* and *Net CF I* respectively) by subtracting to each payment the costs and the portion of the recovery amount given to the recovery agent. Notice that for this example we set the fixed costs arbitrarily to 10€ per each cash flow. This estimate has to be done by the operator and should comprehend the administrative costs and the cost of the personnel.

After this, we need to model cash flow across time, as shown from the first rows of *Table 16*. Notice that the periods are different for each capital bin the credit belongs to. Once cash flows are timely distributed, they are discounted by the targeted discount rate for each period. This leads to the present value (PV) of each cash flow. In the example, cash flows are discounted for the three different discount rates of 9%, 12% and 15%, in order to offer a range for the price.

To obtain the expected present value of each security, we then sum all the actualized cash flows and multiply it by the probability of recovery. The result is the price of each credit, that summed together returns the price of the basket of credits (corresponding to the *Price* columns of *Table 16*). The whole process of the discounted cash flow model is summarized on the *Table 16*.

The example explains how to calculate the price of a basket of past due credits based on the model proposed.

In order to offer a comparison, the present values of the securities above are calculated according to the actual data of the movements dataset. They are then discounted by a 12% discount rate. The value obtained is equal to 7,203.87€, close to the estimated price and inside the confidence range.

Notice that the model, i.e. the code in Python for the model calculation, is flexible, meaning that it allows to change some variables that may vary according to the structure of the company. More specifically they are:

- The years until the first cash flow, in case the company has a lower workload and is able to focus on the new acquired credits;
- Extraordinary costs, that may vary both due to the company's structure or to specific aspects of the credits, such as the presence of abundant and reliable information;

- The incentive to agent, in case the company offers an average different commission or is organized to rely mainly on the phone collection.

As highlighted by the example, the model offers a valuable tool to price a basket of past due credits. Moreover, the coefficients of the two regressions are useful indication on what are the main drivers of the recovery. Knowing the positive influence of some variables allow operators to target some securities that are more likely to be recovered, if the coefficients of the logistic regression are taken into account, or that yield a higher recovery rate, it the coefficients of the OLS are indeed considered.

| Period | C_BIN | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *T1* | 5 | 4.9 | 5.02 | 5.14 | 5.25 | 5.37 | 5.49 | 5.61 | 5.72 | 5.84 | 5.96 | 6.08 | 6.2 | 6.31 | 6.43 | 6.55 | 6.67 | | |
| *T2* | 3 | 4.4 | 4.52 | 4.64 | 4.75 | 4.87 | 4.99 | 5.11 | 5.22 | 5.34 | 5.46 | 5.58 | 5.7 | 5.81 | 5.93 | 6.05 | | | |
| *T3* | 2 | 3.8 | 3.92 | 4.04 | 4.15 | 4.27 | 4.39 | 4.51 | 4.62 | 4.74 | 4.86 | 4.98 | 5.1 | 5.21 | | | | | |
| *T4* | 5 | 4.9 | 5.02 | 5.14 | 5.25 | 5.37 | 5.49 | 5.61 | 5.72 | 5.84 | 5.96 | 6.08 | 6.2 | 6.31 | 6.43 | 6.55 | 6.67 | | |
| *T5* | 5 | 4.9 | 5.02 | 5.14 | 5.25 | 5.37 | 5.49 | 5.61 | 5.72 | 5.84 | 5.96 | 6.08 | 6.2 | 6.31 | 6.43 | 6.55 | 6.67 | | |
| *CF1* | 5 | 861.43 € | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | 883.55 | | |
| *CF2* | 3 | 225.36 € | 240.58 | 240.58 | 240.58 | 240.58 | 240.58 | 240.58 | 240.58 | 240.58 | 240.58 | 240.58 | 240.58 | 240.58 | 240.58 | 240.58 | | | |
| *CF3* | 2 | 77.71 € | 93.12 | 93.12 | 93.12 | 93.12 | 93.12 | 93.12 | 93.12 | 93.12 | 93.12 | 93.12 | 93.12 | 93.12 | 93.12 | | | | |
| *CF4* | 5 | 245.06 € | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | 267.18 | | |
| *CF5* | 5 | -32.12 € | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | |
| ***DisRate*** | **5** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **12.00%** | **Total PV** | **Price** |
| *PV1* | 5 | 494.37 € | 500.21 € | 493.46 € | 487.34 € | 480.76 € | 474.27 € | 467.86 € | 462.07 € | 455.82 € | 449.67 € | 443.59 € | 437.60 € | 432.18 € | 426.34 € | 420.58 € | 414.90 € | 7,341.05 € | 4,874.45 € |
| *PV2* | 3 | 136.87 € | 144.14 € | 142.20 € | 140.43 € | 138.54 € | 136.67 € | 134.82 € | 133.15 € | 131.35 € | 129.58 € | 127.83 € | 126.10 € | 124.54 € | 122.86 € | 121.20 € | 0.00 € | 1,990.27 € | 597.08 € |
| *PV3* | 2 | 50.52 € | 59.72 € | 58.91 € | 58.18 € | 57.40 € | 56.62 € | 55.86 € | 55.16 € | 54.42 € | 53.68 € | 52.96 € | 52.24 € | 51.60 € | 93.12 € | 0.00 € | 0.00 € | 810.39 € | 661.28 € |
| *PV4* | 5 | 140.64 € | 151.26 € | 149.22 € | 147.37 € | 145.38 € | 143.42 € | 141.48 € | 139.73 € | 137.84 € | 135.98 € | 134.14 € | 132.33 € | 130.69 € | 128.92 € | 127.18 € | 125.46 € | 2,211.03 € | 1,308.93 € |
| *PV5* | 5 | -18.43 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | -18.43 € | -2.65 € |
| | | | | | | | | | | | | | | | | | | **12,334.30 €** | **7,439.09 €** |
| ***DisRate*** | **5** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **9.00%** | **Total PV** | **Price** |
| *PV1* | 5 | 564.72 € | 573.26 € | 567.36 € | 562.01 € | 556.23 € | 550.50 € | 544.84 € | 539.70 € | 534.15 € | 528.65 € | 523.21 € | 517.83 € | 512.94 € | 507.67 € | 502.44 € | 497.27 € | 8,582.78 € | 5,698.96 € |
| *PV2* | 3 | 154.24 € | 162.96 € | 161.29 € | 159.77 € | 158.12 € | 156.50 € | 154.89 € | 153.42 € | 151.85 € | 150.28 € | 148.74 € | 147.21 € | 145.82 € | 144.32 € | 142.83 € | 0.00 € | 2,292.23 € | 687.67 € |
| *PV3* | 2 | 56.01 € | 66.42 € | 65.74 € | 65.12 € | 64.45 € | 63.79 € | 63.13 € | 62.54 € | 61.89 € | 61.26 € | 60.63 € | 60.00 € | 59.44 € | 93.12 € | 0.00 € | 0.00 € | 903.54 € | 737.29 € |
| *PV4* | 5 | 160.65 € | 173.35 € | 171.57 € | 169.95 € | 168.20 € | 166.47 € | 164.76 € | 163.20 € | 161.52 € | 159.86 € | 158.22 € | 156.59 € | 155.11 € | 153.52 € | 151.94 € | 150.37 € | 2,585.26 € | 1,530.48 € |
| *PV5* | 5 | -21.06 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | -21.06 € | -3.03 € |
| | | | | | | | | | | | | | | | | | | **14,342.75 €** | **8,651.36 €** |
| ***DisRate*** | **5** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **15.00%** | **Total PV** | **Price** |
| *PV1* | 5 | 434.31 € | 438.05 € | 430.77 € | 424.20 € | 417.14 € | 410.20 € | 403.38 € | 397.23 € | 390.62 € | 384.12 € | 377.74 € | 371.45 € | 365.79 € | 359.70 € | 353.72 € | 347.84 € | 6,306.27 € | 4,187.36 € |
| *PV2* | 3 | 121.84 € | 127.91 € | 125.78 € | 123.86 € | 121.80 € | 119.78 € | 117.79 € | 115.99 € | 114.06 € | 112.16 € | 110.30 € | 108.46 € | 106.81 € | 105.03 € | 103.29 € | 0.00 € | 1,734.87 € | 520.46 € |
| *PV3* | 2 | 45.69 € | 53.84 € | 52.94 € | 52.14 € | 51.27 € | 50.42 € | 49.58 € | 48.82 € | 48.01 € | 47.21 € | 46.43 € | 45.65 € | 44.96 € | 93.12 € | 0.00 € | 0.00 € | 730.08 € | 595.75 € |
| *PV4* | 5 | 123.55 € | 132.46 € | 130.26 € | 128.27 € | 126.14 € | 124.04 € | 121.98 € | 120.12 € | 118.12 € | 116.16 € | 114.22 € | 112.33 € | 110.61 € | 108.77 € | 106.96 € | 105.18 € | 1,899.20 € | 1,124.32 € |
| *PV5* | 5 | -16.19 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | 0.00 € | -16.19 € | -2.33 € |
| | | | | | | | | | | | | | | | | | | **10,654.22 €** | **6,425.56 €** |

## 8. Conclusions

The dissertation describes a model to estimate the price of past due credits. This result is achieved first by estimating the two key metrics of the model: the probability of recovery through a logistic regression, followed by the estimate of the amount recovered by estimating the recovery rate with an OLS regression. Finally, the timing of the recovery and the associated costs are obtained by analyzing five different ranges of capital. Once all these inputs are obtained, the price of a basket of past due credits can be obtained through the discounted cash flow model.

The purpose of the model is to obtain the expected net present value of a basket of non-performing unsecured credits issued to retail client. Furthermore, all credits in the sample are positions sold by the original owner. Purchased credits usually contain little information about the debtor and its past payment behavior, making it hard for the buyer to estimate the expected revenue from the transaction.

The difficulty regarding the estimate of the price has a major impact on SMEs operating in the credit recovery or in the factoring sectors. Such companies usually do not have a specific division or a professional dedicated to auditing past due credits. Because of this, the model tries to generate an estimate of such values in an environment where low information is available.

To achieve this result, the first step was to define the different types of past due loans and their legal treatment. After this, a wider approach was adopted, focused on the description of the Italian market of non-performing credits, adopting at first the sell-side point of view, made of lending financial entities and factoring companies. More specifically, we have described the incidence of NPLs and other types of past due debt on the balance sheet of financial and corporate entities.

As described by Pwc in its annual report about the Italian NPL market, an important evidence we obtained is the decreasing trend of the stock of NPLs started after the peak reached in 2015, at an average rhythm of -16% per year (Pwc, 2018). The reduction pattern is the consequence of the purchase of past due credits by specialized speculative players such as hedge funds or other financial institutions. Moreover, the reviewed literature highlights how credits belonging to this asset class are evenly distributed alongside the Peninsula. In fact, the regions displaying a higher density of past due credits are northern regions, that tend to be more populated and more productive regions, such as Lombardy, Veneto, Trentino and Piedmont. However, those regions show a lower gross bad loans ratio if compared to southern regions (Pwc, 2018). Southern regions and the islands of Sicily and Sardinia have indeed a higher gross bad loans ratio, even if the overall volume tends to be relatively small.

These past due credits are the fuel for credit recovery agencies, i.e. the final actor of the buy-side. Another sector that acts as supplier for credit recovery companies is the factoring industry. Also, it is not unusual for credit recovery companies to buy directly basket of credits from corporate and financial entities through factoring operations. As highlighted in the dissertation, the industry is on a robust increasing path in terms of annual volume and turnover, acting as an alternative credit supplier for companies and professionals.

The increasing trend of the selling of NPLs, together with a higher volume of factoring transactions, have a positive reflection on the activity of credit recovery agencies in terms of entrusted cases, according to UNIREC (Centro Studi UNIREC, 2019). The credit recovery sector in fact is growing, both in terms of revenue and of volume entrusted.

Sell-side credits, i.e. the side of the market that supplies past due credits, are reviewed also in terms of the debtors' origin, meaning its nature or sector where it operates. Regarding non-performing-loans (NPL) and unlikely-to-pay (UtP) credits, most debtors are corporate entities (72%), followed by individuals (22%). Similar results are found for the factoring market, where corporate debtors are the majority of the category (56%), followed by the PA (18.6%) and individuals (4.8%).

Regarding the nature of the creditors, the factoring sector sees a high presence of corporate and SME creditors (76%), and financial entities (12%). NPL and UtP credits are indeed credits originally issued by financial institution.

This reflects on the composition of the clients of credit recovery agencies. As reported by UNIREC, the highest portion of creditors have a corporate origin (51%) followed by financial entities (42%) and the PA (7%). The scenario changes if we consider the creditor shares per amount entrusted. In this case the highest share of creditors is represented by financial institutions (67%) followed by corporate entities and SME (30%). We can see that SME and credit recovery agencies, many of which have small sizes, play an important role in the market of past due credits. This gives evidence on how a quantitative model can be necessary to companies to obtain the estimate of the price of past due securities.

To estimate the price of a basket of past due positions, is essential to understand the core process of debt recovery. The description of the different aspects of the recovery process is essential when estimating key factors, such as the stream of cash flows and connected costs and how they are timely distributed. Also, an important element to highlight when dealing with the process of debt recovery is the difference between the legal recovery and the extra-judicial procedure. In particular, the literature shows that the legal recovery tends to be more expensive both in terms of time and legal costs, and it often requires elements typical of the extra-judicial process, like the investigation on the debtor's financial situation. Considering this, the more efficient approach seems to be a mixed one, where the extra-judicial recovery is used in first stage and, when it does not lead to the collection of the unpaid capital from the debtor, it offers enough information about the solvability of the debtor in order to eventually use the legal approach.

Once a general overview of the Italian market for past due credits is offered, considering both the buy and the sell-side of the market, we examine our dataset. The first step was to offer a descriptive analysis of the main variables of the sample.

We then estimated the two important metrics that are the key elements of our model: the expected recovery rate and the probability of recovery.

The probability of recovery is estimated through a logistic regression. The model draws important results on how some variables have a positive or negative impact on the likeliness of the recovery. In particular, the significant variables are the gender of the debtor, its geographical location and specific elements of the credits such as the amount of capital and interest. Moreover, these results can be useful not only to estimate the price of a basket of credits, but also to other internal activities of credit recovery agencies, such as to prioritize the recovery of certain positions instead of others.

We have found that the variables that have a positive impact on the likelihood of the recovery are:

- The gender of the debtor, in the sense that the recovery is more likely if the debtor is a woman;
- The year of selling of the credit, meaning that more recently issued credits tend to be easier to recover;
- The interest-over-capital ratio, where the higher is the proportion, the more likely is the recovery;
- The presence of an asset as underlying to the credit. In our specific case, the underlying asset refers to automobiles;
- The location of the debtor, where the recovery is more likely if the debtor's residency is from a northern or central region of the Peninsula;

The variables that indeed have a negative impact on the probability of the recovery are:

- The age of the debtor;
- If the debtor moved from its original region of birth;
- The capital amount, meaning that the higher is the capital, the lower is the probability of recovery;
- If the credit has a financial credit;
- The location of the debtor, in case its residency is from a southern region of the Peninsula or abroad.

Similar results can be drawn for the OLS regression. The multiple linear regression is a step that follows the logistic regression and is used to estimate the magnitude of the recovery. It shows the influence that each variable has on the overall recovered amount, while the logistic regression estimates the likeliness of the recovery, considering the described variables.

As for the logit regression, the results of the OLS regression can be useful to enhance other processes of debt recovery agencies since it highlights those elements that have a greater impact on the amount recovered.

The variables that have a positive impact on the magnitude of the recovery are:

- the employment rate of the residency region of the debtor when the dossier is purchased;
- the projected number of payments, meaning that more deferred payments lead to a higher overall result;
- the gender of the debtor in the sense that the recovery is more likely if the debtor is a woman;
- the presence of an underlying to the credit issuance, that in our sample correspond to automobiles;
- the year of closing of the dossier in the sample, i.e. the year where the last payment is completed, meaning that more recent debts yields a higher recovery rate;

Notice that the year of closing of the dossier is a variable that is not accessible at the moment of purchasing of the credit since it refers to the future event of the recovery. The aim of the variables is to reflect the economic situation in a certain point of time. Considering this, when estimating the price of the securities, the year of closing should be represented by the year of issuance of the credit or by the year of the first selling of the credit, if it does not come from its original owner.

The variables that indeed show a negative impact on the total recovered amount are:

- if the debtor has moved from its original region of birth;
- the capital amount, meaning that the higher is the capital amount, the lower is the recovery rate;
- general consumer credits, not issued for the purchase of a specific item;

The region of residency of the debtor has a variable effect on the recovery rate that is not related to areas such as northern, southern or central region.

Finally, after estimating the time distribution and the different costs connected to each cash flow the model allows to estimate the price of a basket of credits. Notice that the model performs efficiently only when evaluating a basket of credits, ideally of a large size, instead of single securities.

Moreover, the results obtained from the OLS and the logit models are valid for securities with characteristics similar to the ones of the sample. In fact, the model is designed to estimate the price of past due credits that are unsecured and that are issued to retail customers. But the methodology can be reproduced to evaluate also different kind of credits.

Not only, the proposed model can be further enhanced in case more information is available.

Other possible improvements to the model is the possibility to use more sophisticated methods to create clusters when estimating the costs and the timing of the recovery. Furthermore, the recovery rate can be modelled nonlinearly with machine learning or other non-linear techniques, as it shows to offer a better performance (Loterman et al., 2012). However, it is a useful tool, especially for small and medium companies operating in the factoring market or in the credit recovery sector.

## 9. Annex 1

This annex reports the detailed results of the logistic regression and stacked-bar graphs showing the influence of the selected variables on the probability of recovery. The results are resumed in the following table:

| | Coef. | Std.Err. | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| Age | -0.0250 | 0.00 | -10.00 | 0.00 | -0.03 | -0.02 |
| Gender_F | 0.2479 | 0.09 | 2.77 | 0.01 | 0.07 | 0.42 |
| Moved | -0.5563 | 0.08 | -6.65 | 0.00 | -0.72 | -0.39 |
| Y_S_Bin | 0.4241 | 0.04 | 11.93 | 0.00 | 0.35 | 0.49 |
| Capital_Bin | -0.0509 | 0.03 | -1.84 | 0.07 | -0.11 | 0.00 |
| Interest over capital | 1.0694 | 0.12 | 8.82 | 0.00 | 0.83 | 1.31 |
| Type_A | 0.2590 | 0.16 | 1.59 | 0.11 | -0.06 | 0.58 |
| Type_B | -0.1458 | 0.16 | -0.91 | 0.36 | -0.46 | 0.17 |
| Residency_South | -0.4303 | 0.11 | -4.07 | 0.00 | -0.64 | -0.22 |
| Residency_Center | 0.0235 | 0.11 | 0.21 | 0.84 | -0.20 | 0.25 |
| Residency_North East | 0.3240 | 0.11 | 2.88 | 0.00 | 0.10 | 0.54 |
| Residency_Abroad | -2.4674 | 1.06 | -2.33 | 0.02 | -4.55 | -0.39 |

*Table 16. Results of the logistic regression. Source: own data.*

As highlighted by the z-values and the associated probability, all variables are significant. The significance is confirmed by the following stacked bars, that shows the portion of debtors belonging to each category that fulfilled their obligations (*figure 23*).

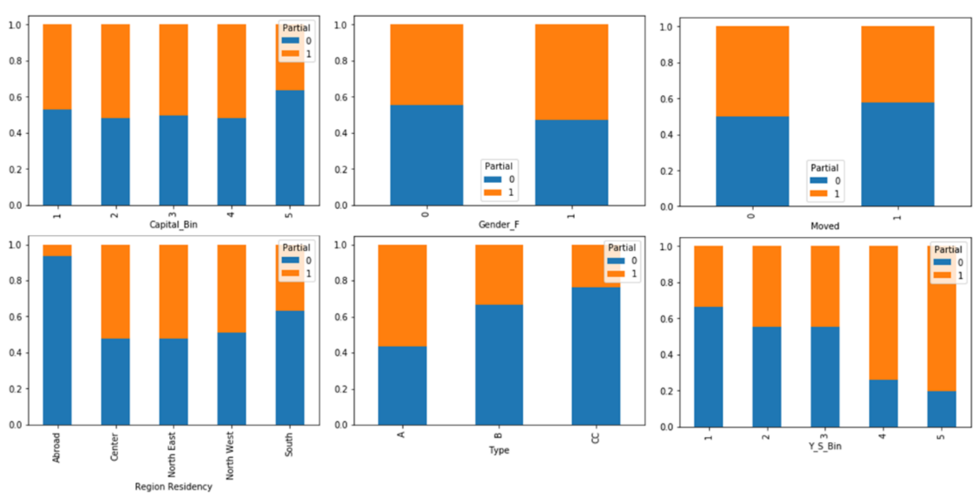



*Figure 23. Stacked bars graph showing the portion of debtors belonging to the different categories (Capital Bin, Gender, Moved Region Residency, Type and Bin of the Year of Selling) that fulfilled their obligations. Source: own data.*

# 10. Annex 2

This annex reports the detailed result of the OLS regression previously presented. Together with the coefficients, the table indicated the p-values and their associated probability, the confidence interval and the VIF of each variable.

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] | VIF |
|---|---|---|---|---|---|---|---|
| *Intercept* | *0.1099* | *0.81* | *0.14* | *0.89* | *-1.47* | *1.69* | |
| **Moved** | -0.0310 | 0.06 | -0.49 | 0.63 | -0.16 | 0.09 | 2.324 |
| **Employment_Y_C** | 0.2491 | 0.49 | 0.51 | 0.61 | -0.71 | 1.21 | 16.204 |
| **Interest over capital** | 0.3788 | 0.05 | 7.63 | 0.00 | 0.28 | 0.48 | 3.760 |
| **N payments** | 0.0177 | 0.00 | 14.42 | 0.00 | 0.02 | 0.02 | 1.757 |
| **Gender_F** | 0.0308 | 0.05 | 0.66 | 0.51 | -0.06 | 0.12 | 1.540 |
| **C_Bin_2** | -0.2861 | 0.07 | -4.13 | 0.00 | -0.42 | -0.15 | 2.056 |
| **C_Bin_3** | -0.4129 | 0.07 | -5.89 | 0.00 | -0.55 | -0.28 | 2.218 |
| **C_Bin_4** | -0.5867 | 0.07 | -8.36 | 0.00 | -0.73 | -0.45 | 2.317 |
| **C_Bin_5** | -0.7319 | 0.07 | -9.94 | 0.00 | -0.88 | -0.59 | 2.494 |
| **Type_A** | 0.1306 | 0.06 | 2.22 | 0.03 | 0.02 | 0.25 | 5.767 |
| **Type_CC** | -0.2160 | 0.14 | -1.50 | 0.13 | -0.50 | 0.07 | 1.385 |
| **Birth_ABRUZZO** | -0.1722 | 0.31 | -0.56 | 0.58 | -0.78 | 0.44 | 1.876 |
| **Birth_AFRICA** | -0.2732 | 0.25 | -1.09 | 0.27 | -0.76 | 0.22 | 3.405 |
| **Birth_AMERICA** | 0.2289 | 0.35 | 0.66 | 0.51 | -0.46 | 0.91 | 1.594 |
| **Birth_ASIA** | -0.5940 | 0.31 | -1.91 | 0.06 | -1.20 | 0.02 | 1.890 |
| **Birth_CALABRIA** | -0.0485 | 0.25 | -0.20 | 0.84 | -0.53 | 0.43 | 3.572 |
| **Birth_CAMPANIA** | -0.1051 | 0.22 | -0.47 | 0.64 | -0.54 | 0.33 | 8.436 |
| **Birth_EMILIA ROMAGNA** | -0.1949 | 0.24 | -0.82 | 0.41 | -0.66 | 0.27 | 5.998 |
| **Birth_EST EUROPE** | 0.0448 | 0.27 | 0.17 | 0.87 | -0.48 | 0.57 | 2.553 |
| **Birth_EUROPE** | 0.0554 | 0.25 | 0.22 | 0.83 | -0.44 | 0.55 | 3.381 |
| **Birth_FRIULI VENEZIA GIULIA** | -0.1350 | 0.24 | -0.57 | 0.57 | -0.60 | 0.33 | 5.230 |
| **Birth_LAZIO** | -0.1289 | 0.23 | -0.57 | 0.57 | -0.57 | 0.31 | 10.450 |
| **Birth_LIGURIA** | 0.1565 | 0.31 | 0.51 | 0.61 | -0.45 | 0.76 | 1.875 |
| **Birth_LOMBARDIA** | -0.0910 | 0.22 | -0.41 | 0.68 | -0.53 | 0.35 | 19.238 |
| **Birth_MARCHE** | -0.0533 | 0.31 | -0.17 | 0.86 | -0.66 | 0.56 | 1.904 |
| **Birth_PIEMONTE** | -0.0312 | 0.23 | -0.13 | 0.89 | -0.49 | 0.43 | 6.448 |
| **Birth_PUGLIA** | -0.1232 | 0.23 | -0.54 | 0.59 | -0.57 | 0.32 | 6.589 |
| **Birth_SARDEGNA** | -0.0048 | 0.26 | -0.02 | 0.99 | -0.51 | 0.50 | 3.120 |
| **Birth_SICILIA** | 0.0349 | 0.22 | 0.16 | 0.87 | -0.40 | 0.47 | 11.808 |
| **Birth_TOSCANA** | 0.1569 | 0.24 | 0.67 | 0.51 | -0.31 | 0.62 | 5.828 |
| **Birth_TRENTINO ALTO ADIGE** | -0.0379 | 0.29 | -0.13 | 0.90 | -0.62 | 0.54 | 2.309 |
| **Birth_UMBRIA** | -0.2796 | 0.31 | -0.91 | 0.37 | -0.89 | 0.33 | 1.898 |
| **Birth_VENETO** | 0.0172 | 0.22 | 0.08 | 0.94 | -0.42 | 0.46 | 10.270 |
| **Y_C_Bin_2** | 0.1033 | 0.07 | 1.55 | 0.12 | -0.03 | 0.23 | 2.018 |
| **Y_C_Bin_3** | 0.1984 | 0.07 | 2.97 | 0.00 | 0.07 | 0.33 | 2.002 |
| **Y_C_Bin_4** | 0.1108 | 0.07 | 1.57 | 0.12 | -0.03 | 0.25 | 1.861 |
| **Y_C_Bin_5** | 0.0909 | 0.07 | 1.37 | 0.17 | -0.04 | 0.22 | 2.126 |

*Table 17. Results of the OLS Regression. Source: own elaboration.*

Moreover, a series of scatterplots are shown in *Figure 24*, highlighting the correlation between the independent variables and the recovery rate.

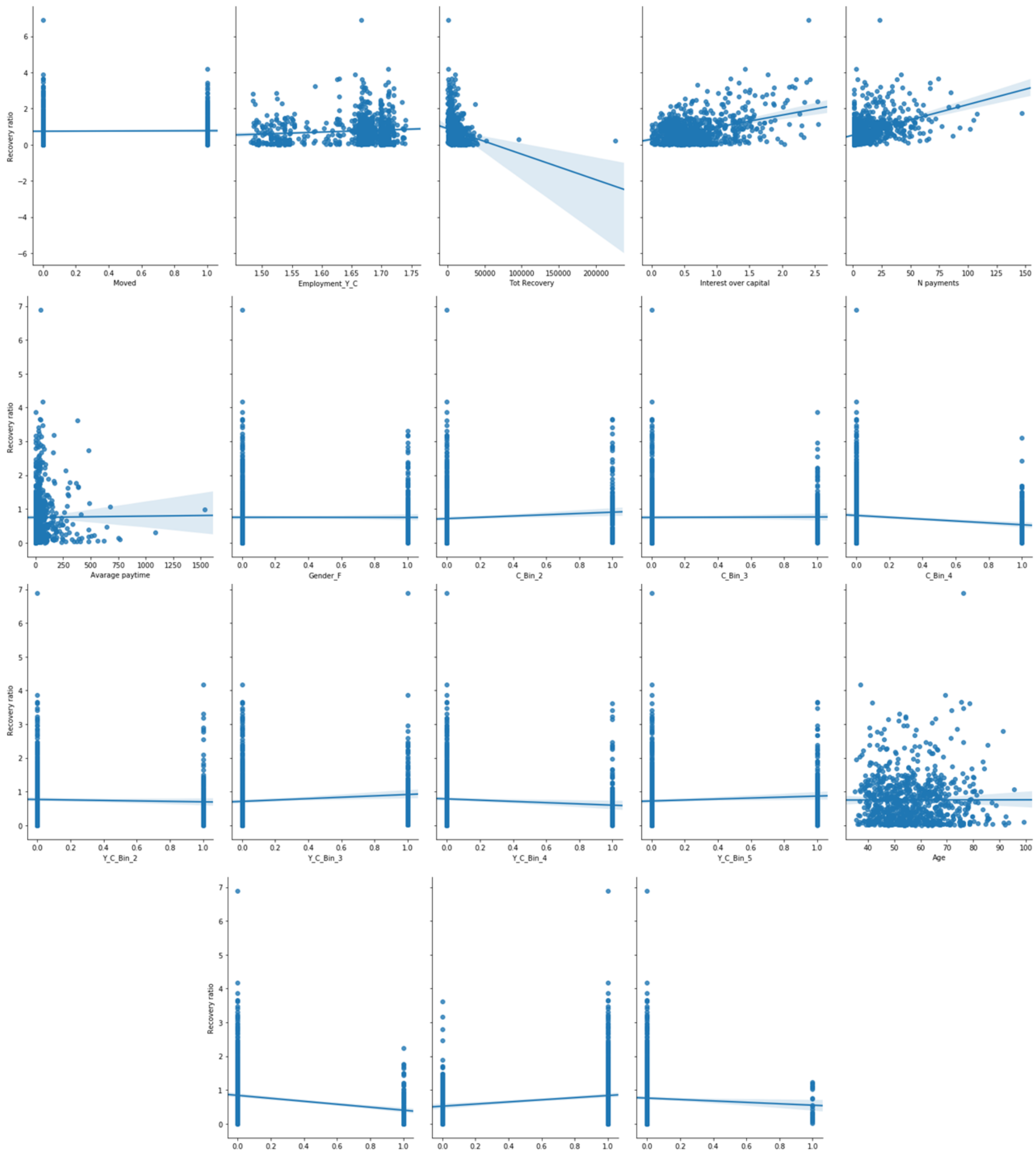



*Figure 24. Scatterplot showing the relation between the independent variables (Capital Bin, Gender, Moved, Average days between each payment, Type, Age and Bin of the Year of Closing) and the recovery rate. Source: own data.*

## References:


A.S. Messai and F. Jouni, Micro and Macro Determinants of Non-performing Loans, International Journal of Economics and Financial Issues, Vol. 3, No. 4, 2013, pp.852-860.

Adriaan M. Bloem and Russel Freeman, The Treatment of Nonperforming Loans, International Monetary Fund, 2005.

Alessandro Carretta, "Indagine sulla Domanda di Factoring", SDA Bocconi, 2009.

Andrea Franceschini, "Prestiti e mutui, perché la cura Bce ha aiutato più le famiglie che le aziende", Il Sole 24Ore, September 2019.

Angelo Paletta, "Il mercato italiano del factoring continua a crescere", March 2019.

Anthony Bellotti and Jonathan Cook, Loss given default models incorporating macroeconomic variables for credit cards, International Journal of Forecasting, 2012.

Assifact, "Il Contratto di Factoring", 2019.

Assifact, CrediFact, Statistical reports, 2015.

Assifact, CrediFact, Statistical reports, 2016.

Assifact, CrediFact, Statistical reports, 2017.

Assifact, CrediFact, Statistical reports, 2018.

Assifact, CrediFact, Statistical reports, 2019.

Banca d'Italia, Consumer Credit Made Easy, 2018.

Banca d'Italia, Report on Financial Stability 2017, 2017.

Banca IFIS, "Cos'è il Factoring", December 2015.

Bank of Italy, Circolare n° 232, 30/07/2008, Updated at December 2018.

Carlo Festa, “Anno record di vendite di Utp e per il mercato del restructuring in Italia", May 2019.

Centro Studi Unirec, Credit Protection Services, IX Annual Report, May 2019.

Centro Studi Unirec, Credit Protection Services, VIII Annual Report, May 2018.

Claudio D'Auria, Il Nuovo Securitisation Framework, dirittobancario.it, Novembre 2018.

Deducibilità perdite su crediti: FiscoOggi, "Requisiti e onere della prova", Agenzia delle Entrate, May 2019.

Doriana Cucinelli, The Impact of Non-performing Loans on Bank Lending Behavior: Evidence from the Italian Banking Sector, Eurasian Journal of Business and Economics, p. 59-71, 2015.

European Banking Authority, Final Report on Final Guidelines on management of non-performing and forborne exposures, EBA, October 2018.

European Central Bank, Guide to Banking Supervision, ECB, September 2014.

European Central Bank, Guido to Banks on Non-Performing Loans, ECB, March 2017.

Fabio Panetta, "Seminario istituzionale sulle tematiche legate ai non performing loans", Camera dei Deputati, VI Commissione Permanente, May 2017.

Faggella and Contini, "I Non Performing Loans Nel Mondo Delle Utilities : Recupero Crediti Ma Non Solo…", 2018.

Fausto Galmarini, "Il mercato del factoring e l'attività associativa", Assifact Annual Convention, 25th June 2019.

G. Nagarajan, R.L. Meyer, Collateral for Loans: When does it matter?, Economics and Sociology Occasional Paper No. 2207, The Ohio State University, February 1995.

Gert Loterman, Iain Brown, Davidd Martens, Christophe Mues and Bart Baesens, Benchmarking regression algorithms for loss given default modeling, International Journal of Forecasting 28, p. 161-70, 2012.

Gianpaolo Luzzi, "Il Recupero Crediti", FAG, 2017.

Hui Ye and Anthony Bellotti, Modelling Recovery Rates for Non-Performing loans, Risks, February 2019.

L. Davi & C. Festa, “Intesa approva l’offerta di Intrum sui crediti deteriorate”, Il Sole 24 Ore, April 2018.

Luca Davi, “Rinasce il mercato dei crediti deteriorati”, il Sole 24 Ore, July 2015.

Lucas Martin and Margie Memmott, Different Types of Credit and How They Impact You, Utah State University, May 2014.

Min Qi and Xinlei Zhao, Comparison of modeling methods for loss given default, Journal of Banking & Finance 35: 2842–55, 2011.

Moyra Longo, "Npl, rischio «bolla» per il mercato dei crediti deteriorati", February 2019.

Nicola Canestrini, "Riscossione dei crediti: atto di diffida, decreto ingiuntivo, precetto. La procedura di riscossione di Equitalia", CanestriniLex, July 2018

Pwc, The Italian NPL Market: Entering a New Era, December 2018

Raffaela Calabrese, Predicting bank loan recovery rates with a mixed continuous-discrete model, Applied Stochastic Models in Business and Industry, 2012

S. Tanasković & M. Jandrić, Macroeconomic and Institutional Determinants of Non-performing Loans, Journal of Central Banking Theory and Practice, pp. 47-62, December 2014