risks

MDPI

Article

A Non-Performing Loans (NPLs) Portfolio Pricing Model Based on Recovery Performance: The Case of Greece

Alexandra Z. Marouli [1,*], Eugenia N. Giannini [2] and Yannis D. Caloghirou [1]

[1] Laboratory of Industrial and Energy Economy, National Technical University of Athens, 15780 Athens, Greece; y.caloghirou@ntua.gr
[2] Laboratory of Law and Technical Legislation, National Technical University of Athens, 15780 Athens, Greece; giannini@mail.ntua.gr
* Correspondence: amarouli@mail.ntua.gr

Abstract: In this paper, a method was proposed for pricing NPL portfolios, which is currently a crucial point in the portfolio transactions between the banks and NPL servicers. The method was based on a simple mathematical model which simulated the collection process of the NPL portfolios considering the debtors' behavioral response to various legal measures (phone calls, extrajudicial notices, court orders, and foreclosures). The model considered the recovery distribution over time and was applied successfully to the case of Greece. The model was also used to predict recovery, cost, and profit future cash flows, and to optimize the collection strategies related to the activation periods of different measures. A sensitivity analysis was also conducted to reveal the most significant factors affecting the collection process.

Keywords: debt collection; debt recovery; legal measures; NPL portfolio evaluation; debtors' behavior modeling; recovery rate

Citation: Marouli, Alexandra Z., Eugenia N. Giannini, and Yannis D. Caloghirou. 2023. A Non-Performing Loans (NPLs) Portfolio Pricing Model Based on Recovery Performance: The Case of Greece. *Risks* 11: 96. https://doi.org/10.3390/risks11050096

Academic Editors: Eliana Angelini, Alessandra Ortolano and Elisa Di Febo

Received: 7 April 2023
Revised: 12 May 2023
Accepted: 15 May 2023
Published: 18 May 2023

1. Introduction

A Non-Performing Loan (NPL) portfolio could be handled by three managing methods (as shown in Figure 1):

(1) By in-house collection;
(2) By being assigned to a legal agency for collection; or
(3) By selling to a servicer.

Method one was initially used by banks when the volume of NPLs was low, but this method is rarely used today. In method two, the NPL portfolio is assigned to a law firm for collection, the law firm applies legal measures, and depending on their efficiency, recovers a fraction of the initial debt. The portfolio owner pays for the various costs of the measures and receives the collected debt minus a success fee for the compensation of the law office.

Method three is the most commonly used method in recent years. A servicer buys NPL portfolios at a negotiated value and assigns the collection to law firms. An NPL servicer is a specialized legal entity that engages in all stages of the NPL lifecycle. The primary objective of the servicer is to collect the payments and manage the NPL's credit assets.

The NPL portfolio's value is a crucial point for negotiations in method three. Thus, it is very useful to have an initial feasible estimation of the net present value of the NPL portfolio based on the collection efficiency, cost, and implementation timeframe.

This paper proposes a simple but effective NPL portfolio pricing model based on the economics of collection performance. The model considers the most significant factors which determine the collection results, for example: the collection strategy, the debtor's behavior, and the financial and institutional environment. The main goal of the model is to estimate the net present value of the debt portfolio, but it also aims to estimate the input and output cash flows with time, according to the collection procedure.

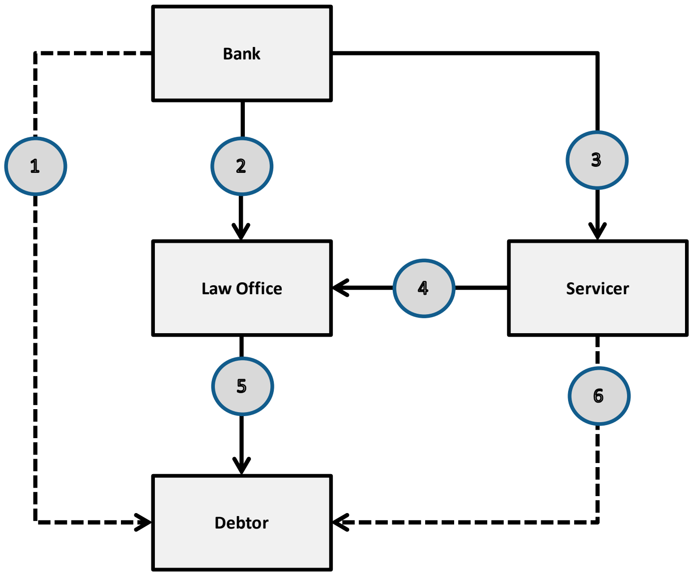


Figure 1. The NPL portfolio management system.

It should be noted that the present analysis does not use the usual black-box approach based on a multiple linear model. Instead, it is based on the use of statistical distributions for the debtors' performance concerning their response to the available legal measures. This alternative approach, taken from an engineering standpoint, constitutes the main innovation of this paper.

Various macroeconomic factors affect the debtors' behavior and, consequently, the debt collection efficiency (Khairi et al. 2021). Government deficit and indebtedness, quantitative easing policies (Cortes et al. 2022), implicit government guarantees (Dantas et al. 2023), and economic policy uncertainty (Bloom 2009; Baker et al. 2016; Campello et al. 2022) can all be influential factors.

This article does not aim to discover the effect of macroeconomic factors on debt recovery. Rather, it aims to predict the future recovery based on the available historical data using a simple fitted model. Substantially, the model combines the macroscopic factors into several model parameters. Thus, the model application is limited to the time and region where the model is fitted. Under that assumption, the model is accurate and sheds light on the important practical problem of NPL portfolio pricing.

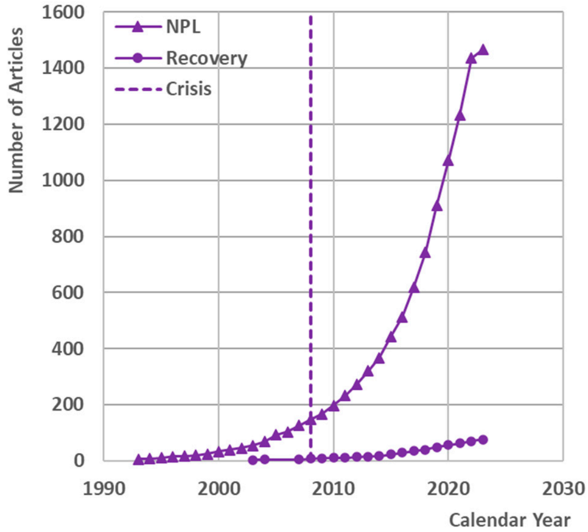
In engineering, it is common to use a simple, imperfect model to obtain accurate predictions after fitting (tuning) it to real data. This concept is often used on-line (that is, as data are produced), and has proven to be efficient in many cases.

We emphasize that the scientific research on NPLs started about 15 years before the global bank crisis of 2008, and has increased exponentially until today. Research on NPL recovery started after the crisis, and has also increased exponentially. Despite this, the amount of research on NPL portfolio pricing is still almost negligible, since the related market developed just a few years ago. Figure 2 shows the trend based on published papers, along with the countries involved.

Multi-factor linear econometric models have been used to determine the effects of various factors, e.g., Beck et al. (2015); Chaibi and Ftiti (2015); Ghosh (2015); Girardone et al. (2004); Messai and Jouini (2013); Dimitrios et al. (2016); Louzis et al. (2012); Makri et al. (2014); Foglia (2022).

Emphasis on recovery and/or pricing is found in the work of Alihodžić and Ekşï (2018); Blanchard and Portugal (2017); Bolognesi et al. (2020a); Chamboko and Bravo (2016); Orlando and Pelosi (2020); Perotti (1993); Scardovi (2015); Stijepović (2014); Bolognesi et al. (2020b); Carleo et al. (2023); Carpinelli et al. (2017); Li et al. (2022); Saulītis (2023); Tupayachi and Silva (2022); Marouli et al. (2015); Bellotti et al. (2021); Calabrese and Zenga (2008); Ye and Bellotti (2019); Manz et al. (2020); Wang et al. (2021).

Authors who have focused on the case of Greece include Karadima and Louri (2020, 2021); Konstantakis et al. (2016); Nikolaidou and Vogiazas (2017); Nikolaidou and Vogiazas (2014); Dimitrios et al. (2016); Louzis et al. (2012); Makri et al. (2014); Marouli et al. (2015).



	Country	Articles
1	France	157
2	China	148
3	United States	129
4	Indonesia	120
5	United Kingdom	120
6	Italy	87
7	Malaysia	86
8	Japan	59
9	**Greece**	**55**
10	Turkey	49
11	Australia	41
12	Viet Nam	40
13	Germany	37
13	Taiwan	37
15	France	32
16	Nigeria	31
16	Pakistan	31

Figure 2. Published papers on non-performing loans and recovery. Data from Scopus (March 2023).

2. Process Description

Depending on the regulations in each country, the collection procedure generally consists of the following measures (Figure 3):

- Phone communication and discussion with the debtor;
- Extrajudicial notification of the debt and debtor obligations;
- Court order of payment;
- Foreclosure in the case of existing real estate properties.

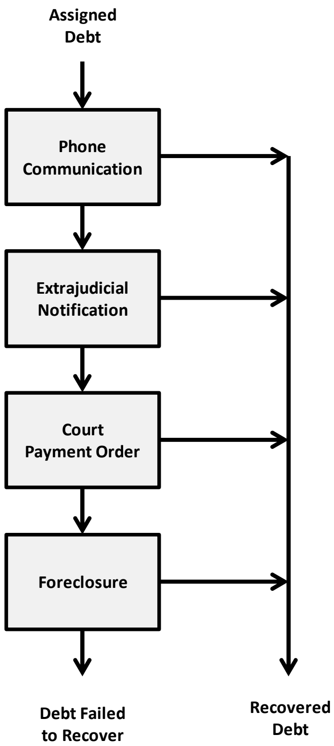


Figure 3. Legal measures applied for debt recovery.

These measures are implemented sequentially, leaving adequate time between the measures to receive the debtors' response. At the beginning of the measure application, some related cost is paid. After some time, some debtors are motivated and some of the debt is paid. According to the debtor's statistical behavior, a wave of payments follows.

3. Process Model

3.1. Targets

The main goal of the model was to estimate the Net Present Value (NPV) of the debt recovered (that is, the NPL portfolio present price) when some critical data are known or can be estimated. The model also aimed to calculate the significant cash flows through time during the time-consuming collection procedure, such as the debt recovery payments, the various costs of the measures, and the overall profit. Furthermore, the model aimed to be appropriate for optimizing the collection procedure.

The model results are summarized as follows:

- The recovery cash flow;
- The measure cost cash flow;
- The profit cash flow;
- The NPL portfolio Net Present Value.

3.2. Factors

The model incorporated the most significant factors affecting the collection process. These factors are summarized and classified below (factors named "Financial and Institutional Data" refer to the general conditions within the process):

- The discount rate, which expresses the time value of money;
- The measure cost, which refers to various measure application costs;
- The success fee for the collection agency.

The "Debtor Behavior" was represented by the following factors:

- The measure efficiency;
- The mode debtor response time;
- The median debtor response time.

The "Collection Strategy" factors referred to various decision variables which are determined by the law firm and/or the portfolio owner:

- The debt fraction for which the measure is applied;
- The time interval for which the measure is kept active.

Based on the above, the information flow diagram is presented in Figure 4.

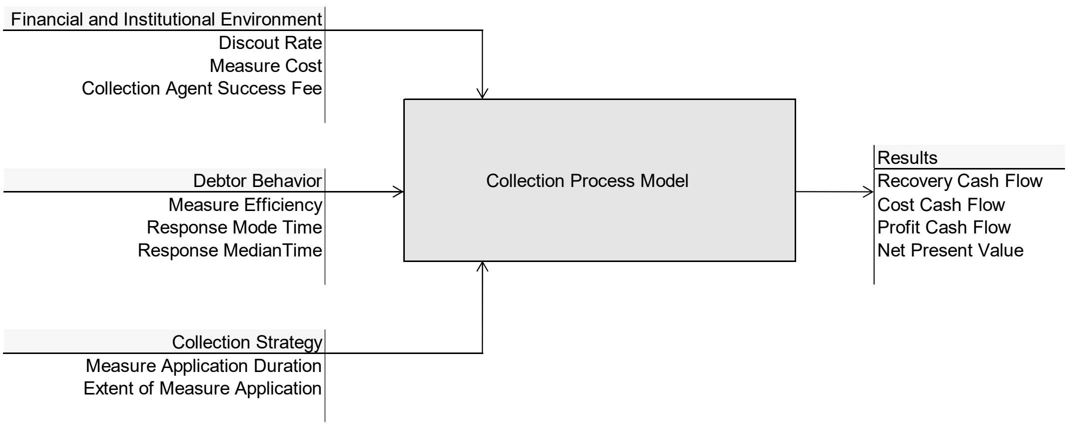


Figure 4. Model information flow diagram.

3.3. Parameter Estimation

Figure 4 suggests that the debtors' behavior depends on three model parameters. These parameters adequately describe the development of recovery, but they do not explain how they depend on the macroeconomic factors described in the introduction.

Thus, in order to use the model, these parameters must be estimated by fitting the model to the historical data; consequently, the model application is limited to the time and region of the data.

Figure 5 explains how the macroeconomic factors are combined into the model parameters, while Figure 6 shows an information flow diagram concerning the parameter estimation procedure.

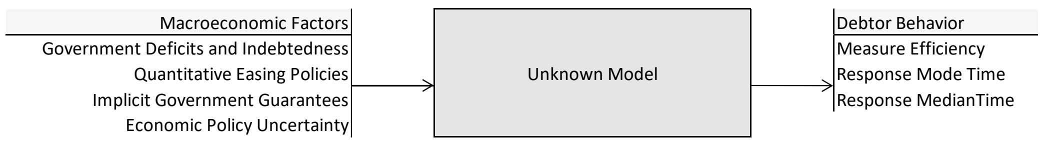


Figure 5. Effect of macroeconomic factors on model parameters.

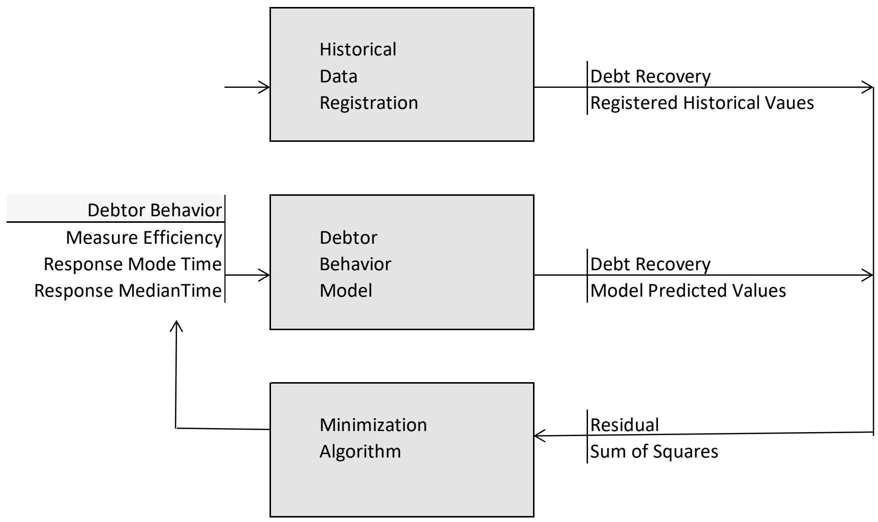


Figure 6. Parameter estimation information flow diagram.

3.4. Process Optimization

Most of the factors listed above are values received from the process environment (e.g., institutional, debtors' performance, market, etc.), and only a few remain at the disposal of the NPL's portfolio manager for process optimization:

- The extent of measure application (the debt fraction for which the measure is applied);
- The measurement duration (the time interval for which the measure is kept active).

The optimum value of measure extent is 1, which represents the measure applied to all debt, except for foreclosure, which is applied only to the debt with collateral (e.g., real estate, etc.).

Thus, optimization means finding the optimum collection time for each measure, considering that the total collection time may be constrained to 3–5 years, depending on the servicer's policies.

Figure 7 presents an information flow diagram for the process optimization, with portfolio Net Present Value as the objective function.

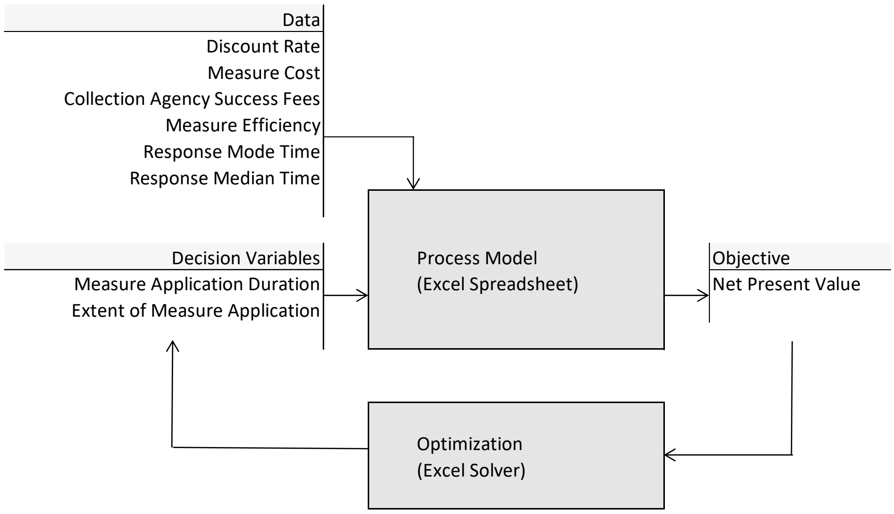


Figure 7. Optimization information flow diagram.

3.5. Model Equations

The measures were implemented sequentially, leaving adequate time between the measures to allow the debtors to respond.

Suppose that a measure i is applied at the time instance t_i. After some time, some debtors are motivated and some of the debt is paid. The debt recovery R_i due to measure i is calculated by the integral:

$$R_i = e_i f_i D_{i-1} \int_{t_i}^{t_{i+1}} r_i(t)\, dt$$

where:

D_{i-1} is the initial unrecovered debt at time t_i when the measure i is applied;
e_i is the extent of measure application;
f_i is the measure efficiency;
$r_i(t)$ is a function which describes the rate of payments versus time.

The extent of measure application e_i expresses the portion of the initial debt D_{i-1} in which the measure is applied. The debt for which the measure is applied is generally lower than the total initial debt D_{i-1} because, in practice, there are cases for which the specific measure cannot be applied. For example, foreclosure cannot be applied in cases that do not involve real estate properties or other collateral.

The measure efficiency f_i is defined as the total amount which can be collected given infinite time divided by the initial debt for which the measure was applied $e_i\, D_{i-1}$.

Only the payments which happen in the time interval between t_i and t_{i+1} are considered as payments due to measure i.

Marouli et al. (2015) proposed a log-normal distribution:

$$r(t) = \frac{1}{t\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(\ln t - \mu)^2}{2\sigma^2}\right)$$

$$\mu = \ln(t_{median})$$

$$\sigma^2 = \ln(t_{median}) - \ln(t_{mode})$$

where t_{median} and t_{mode} are the distribution characteristics.

The response mode time t_{mode} is the point in time corresponding to the maximum payment rate (Figure 8), while the response median time t_{mode} is the point in time by which 50% of the maximum recoverable amount has been obtained (Figure 8).

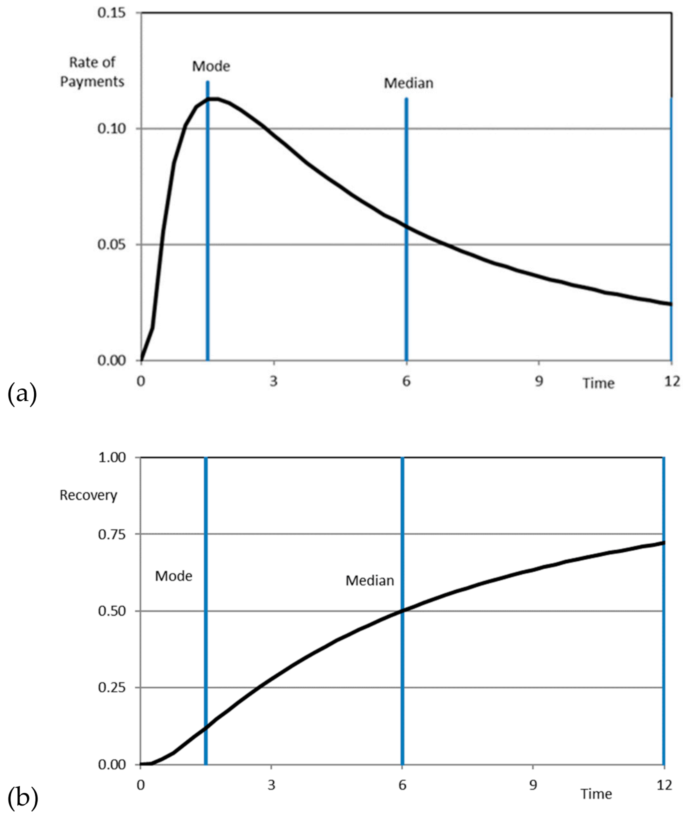


Figure 8. Measure recovery: (**a**) Recovering rate; (**b**) Cumulated recovery.

Marouli et al. (2015) fitted the model to real data, and for each measure they estimated the three crucial parameters (measure efficiency, mode response time, and median response time) which describe the debtor's response to four measures (phone call, extrajudicial notification, order, and foreclosure).

The unrecovered debt D_i at the end of the application of measure i is:

$$D_i = D_{i-1} - R_i$$

The application cost of measure i consists of two separated costs: (a) the institutional cost C_{Mi} and (b) the law agent success fee C_{Si}. Institutional cost is proportional to initial unrecovered debt D_{i-1}, while the law firm success fee is analogous to recovered debt R_i:

$$C_{Mi} = c_i e_i D_{i-1}$$

$$C_{Si} = s_i R_i$$

where:

c_i is the institutional cost coefficient of measure i

s_i is the law agent success fee coefficient for measure i

Generally, the institutional cost c_i further consists of two parts, one of which is constant per case and one of which is analogous to the case loan, that is:

$$c_i = \frac{c_{bi} + c_{mi} L_m}{L_m}$$

where:

c_{bi} is the cost constant per case;

c_{mi} is the cost analogous to case loan;

L_m is the average loan of the portfolio, that is, the total debt per number of cases.

It must be noted that the measure institutional cost C_{Mi} is paid at the time t_i, while the law office success fee cost C_{Si} follows the time variation of debt recovery R_i.

The profit measure P_i, that is, the net debt recovery, is obtained by subtracting the various collection costs C_{Mi} and C_{Si} from the debt recovery R_i:

$$P_i = R_i - C_{Mi} - C_{Si}$$

The total collection profit is:

$$P = \sum_{i=1}^{4} P_i$$

Collection profit is a function of time, and so future payments could be discounted to present value (NPV) using the equation:

$$NPV = \int_0^t \frac{P(t)}{(1+i_d)^t}\, dt$$

where:

t is the time;

i_d is the discounted rate, expressing the time value of money.

The Net Present Value (NPV) of an NPL portfolio is essentially its fair price. It is a crucial point for NPL purchase negotiations.

Figure 9 is a schematic representation of the profit resulting from the measure.

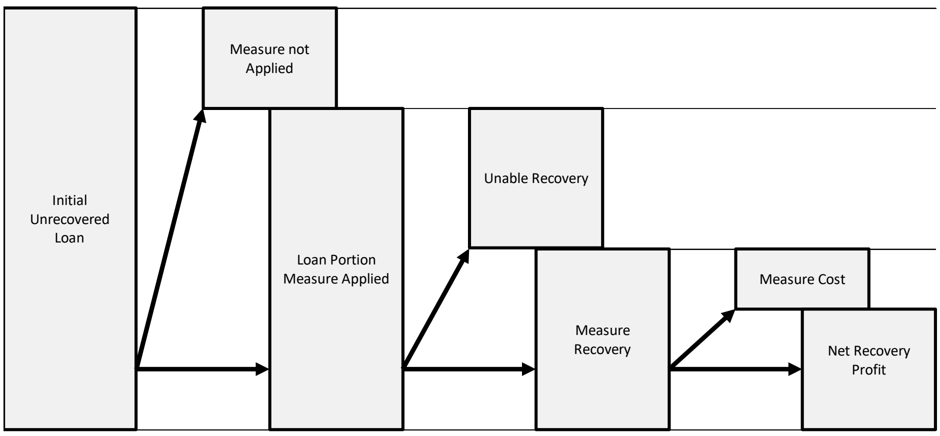


Figure 9. Schematic representation of loan, recovery, cost, and profit cash flows.

3.6. The Case of Greece

Two kinds of data were needed: (a) the debtors' behavior characteristics and (b) the measure cost data.

In a previous paper, Marouli et al. (2015) presented a large set of data from Greece regarding the debtors' behavior. It consisted of 170,000 real cases from systemic Greek banks (personal loans and credit cards). The data referred to both the pre-Greek-crisis period (2003–2007), which was marked by sustainable economic growth, and the Greek crisis period (2008–2012).

A log-normal distribution was proposed and validated using the available data to reveal the debtors' behavior concerning the applied measures (phone calls, extrajudicial notification, payment orders, and foreclosure). The results are summarized in Table 1 and are used in this present analysis.

Table 1 describes the debtors' characteristics using (a) the measure effectiveness, (b) the mode time (at which the maximum rate of payments occurs), and (c) the median time (at which 50% of the overall collected amount is obtained). Data are shown for both growth and recession periods.

Table 2 describes the costs of measures. Data was collected from the relevant legislation along with an appropriate questionnaire answered by some related specific law offices.

Table 1. Debtors' behavior model characteristics (Marouli et al. 2015), Greece 2003–2012.

	Phone	Extrajudicial	Order	Foreclosure
Expansion				
Recovery (%)	8.40	23.6	28.0	100
Mode (mo)	1.48	3.20	1.34	2.54
Median (mo)	4.44	22.8	19.1	25.2
Recession				
Recovery (%)	4.90	11.4	17.9	18.6
Mode (mo)	0.12	1.90	0.13	2.44
Median (mo)	1.80	11.6	43.5	12.5

Table 2. Measure cost data, Greece 2020.

1. Law Office						
1.1 Success Fees	15	% of Recovery				
2. Extrajudicial						
2.1 Real Estate Check	45	€ per Case				
2.2 Notification	30	€ per Case				
3. Court Order						
3.1 Court Fees	1	% of the Loan				
3.2 Lawyer Compensation	64	€ for Loan less than	12,000	€		
	139	€ for Loan between	12,000	and	20,000	€
	268	€ for Loan greater than	20,000	€		
3.3 Notification	20	% of the Loan				
4. Foreclosure						
4.1 Registration of Encumbrance	1.72	% of the Loan				
4.2 Court Fees	150	€ per Case				
4.3 Bailiff Compensation	53	€ for the loan portion less than	590	€		
	2.50	% for the loan portion between	590	and	6500	€
	1.00	% for the loan portion between	6500	and	42,200	€
	0	% for the loan portion greater than	42,200	€		

4. Results and Discussion

The proposed model was simple; it could easily be supported even by Excel, and can be used to solve various typical problems during the collection process, such as preliminary portfolio pricing, predictions of future collection cash flow, optimal measures activation periods, etc.

This section presents a "Base Case" corresponding to the situation in Greece during recent years. It suggests some actions that could optimize the process, and reveals the effect of crucial factors on the collection results.

4.1. Base Case

A "Base Case" scenario is presented in Table 3 and Figure 10, and is defined as follows:

- The NPL portfolio consisted of personal loans and credit cards;
- The size of the loans had a medium average of about EUR 7500/case;
- Collaterals existed for 25% of the loans;
- Cost data were according to recently updated Greek legislation;
- Debtors' behavior was according to the period of economic expansion in Greece;
- The collection period of 5 years was divided equally into 15 months per measure;
- The time value of money was 10% discount rate.

Table 3 presents the input/output data of the model for the Base Case scenario, separately for every legal action. Since the data for the financial and institutional environment were typical for the present period, the debtors' behavior parameters were estimated using recent data, and the collection strategy expressed the typical practice; the results could be considered as a benchmark case. That is, 34.3% of the initial debt could be collected after 5 years, 8.3% of the initial debt corresponded to the various costs of collection, and the resulting net profit was estimated to be 26.0%, which corresponded to 20.9% net present value.

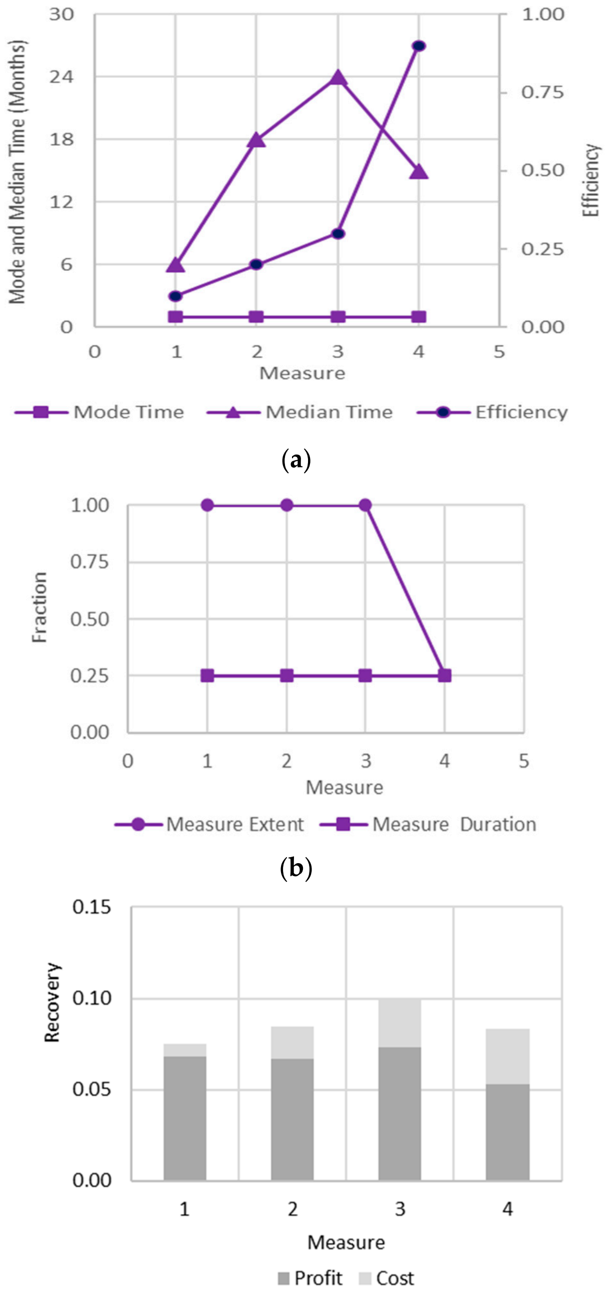
Figure 10 shows the information graphically for every legal action. The legal measure collection efficiency and cost are compared in Figure 10c.

Figure 11 is a complete integrated picture of the collection process cash flows for the entire 60-month collection period. It could be used as a guide for collection offices to evaluate their efficiency and improve their strategy. It shows the waves of successive payments in current and discounted values.

Moreover, Figure 11 presents the evolution with time of the critical collection variables (collection recovery, cost, and profit) for 0% and 10% discount rates.

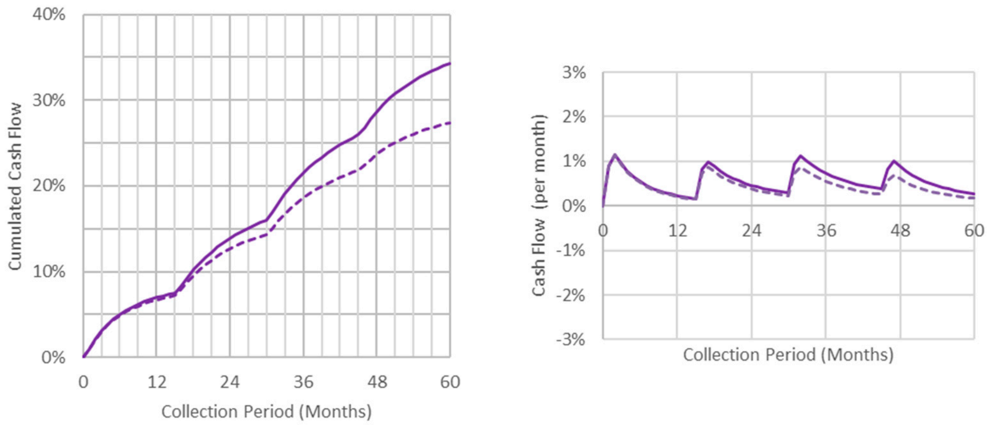
Table 3. Base Case Scenario: Model Input Data and Results.

	Total Collection	Phone	Extra-Juditial	Court Order	Fore-Closure	Units
Model Input Data						
Case Study	Base Case					
Average Loan Size	7500					€/Case
Financial and Institutional Environment						
Measure Constant Cost		0	75	75	150	€/Case
Measure Variable Cost		0.00	0.00	0.01	0.10	% Loan
Collection Agent Success Fee	0.10					% Recovery
Discount Rate	0.10					%
Debtors Behavior Characteristics						
Efficiency		0.10	0.20	0.30	0.90	%
Mode Time		1	1	1	1	Months
Median Time		6	18	24	15	Months
Collection Strategy						
Measure Extent		1.00	1.00	1.00	0.25	%
Measure Duration		0.25	0.25	0.25	0.25	% Total
Total Collection Processing Time	60					Months
Model Results						
Recovery	0.343	0.075	0.085	0.100	0.083	%
Cost	0.083	0.008	0.018	0.027	0.031	%
Profit	0.260	0.068	0.067	0.073	0.053	%
Net Present Value	0.209					%

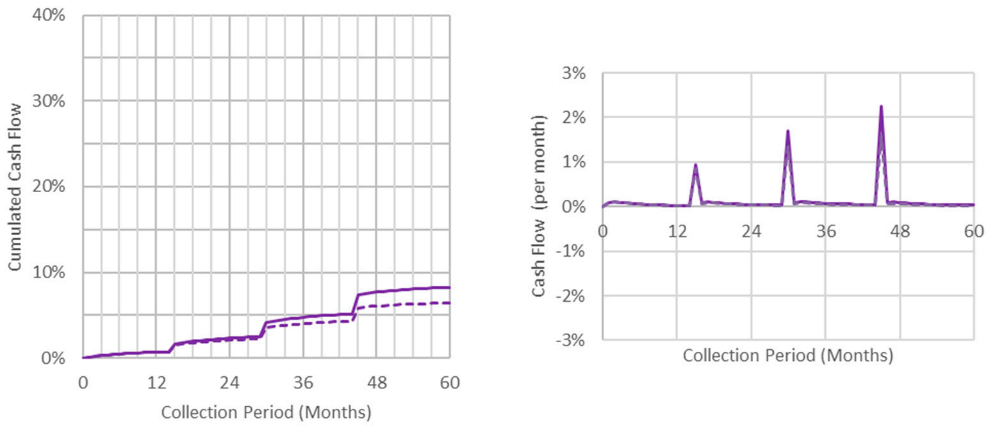


(**a**) (**b**) (**c**)

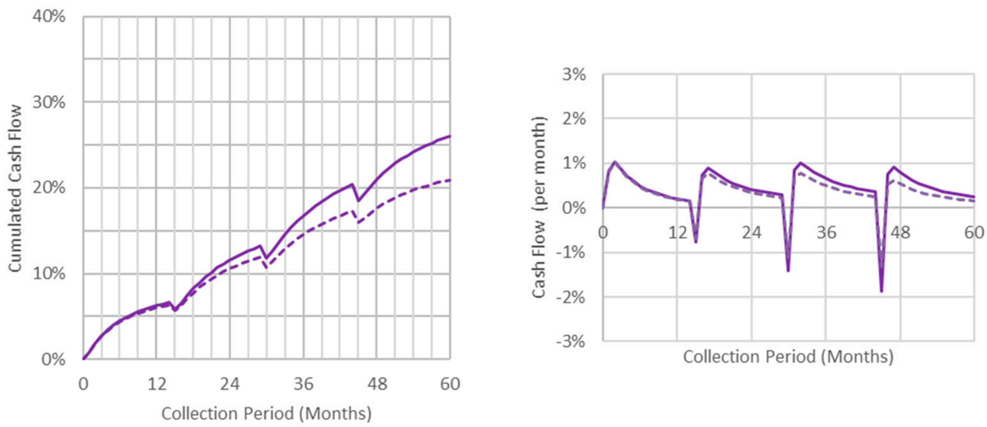
Figure 10. Base case scenario: (**a**) debtors behavior characteristics, (**b**) collection strategy characteristics, (**c**) resulting collection efficiency and cost. Legal measures: (1) phone communication, (2) extrajudicial notice, (3) court order of payment, (4) foreclosure.



(**a**)



(**b**)



(**c**)

Figure 11. Base case scenario: Recovery (**a**), cost (**b**), and profit (**c**) versus time. Discount Rate: 0% (continuous line) and 10% (dotted line).

4.2. Optimization

For the Base Case Scenario, the total collection profit (objective function) was optimized by varying the measure activation times (decision variables); the results are presented in Figure 12. The results suggest that, by decreasing the phone activation time from 15 to 8 months and increasing the court order activation time from 15 to 22 months, the resulting optimized profit becomes 26.7% instead of 26.0%. In this optimum case, the 2.7% improvement in the total collection profit was small but not negligible.

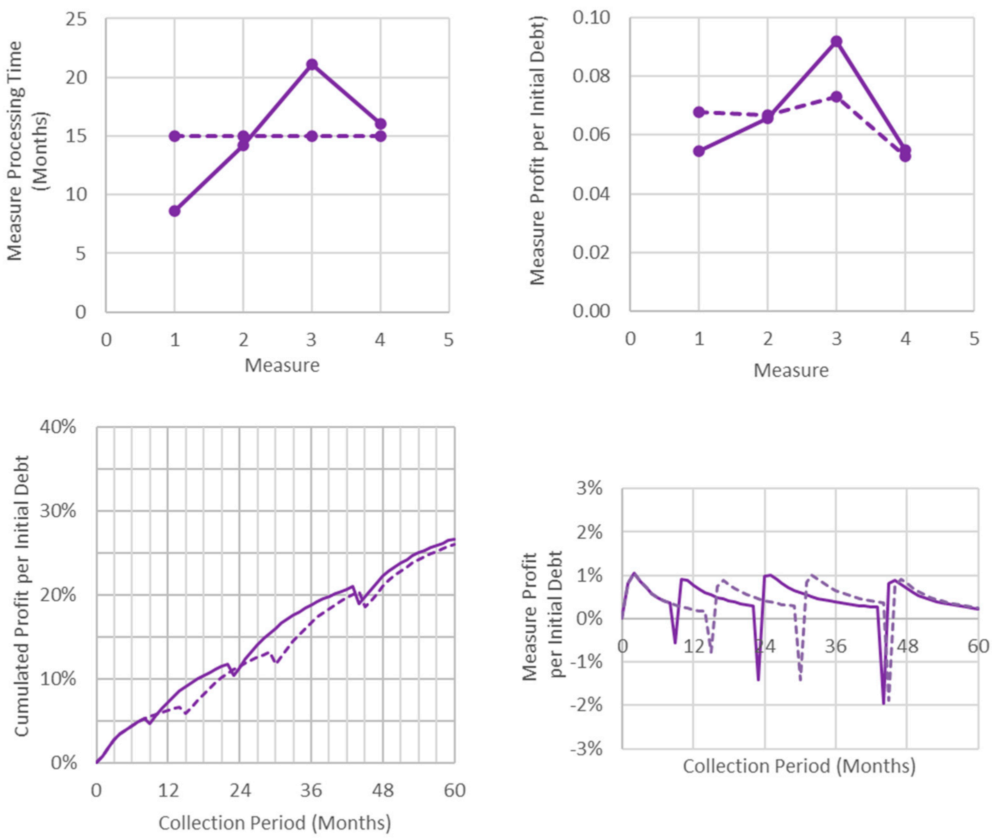


Figure 12. Optimal measure processing time (continuous line) in comparison with equal measure processing time (dotted line).

4.3. Sensitivity Analysis

A sensitivity analysis was conducted in order to explore the effect of the factors on the total profit during the lifetime of a collection process. The results are presented in Figure 13, using both spider and tornado diagrams.

Debt Characteristics

The "Average Loan size" affected the cost data since a part of the cost was analogous to the loan size, but the resulting total effect on the profit proved to be limited. Instead, as expected, the "Collateral Fraction" of the loans played the most important role in the collection process, since the effective foreclosure measure could be applied only to loans with collateral.

Debtors Behavior

Debtors' behavior is described mathematically by three parameters. Both "Measure Efficiency" and "Measure Median Time" play a significant role in the total profit. Conversely, "Measure Mode Time" appears to have a negligible effect.

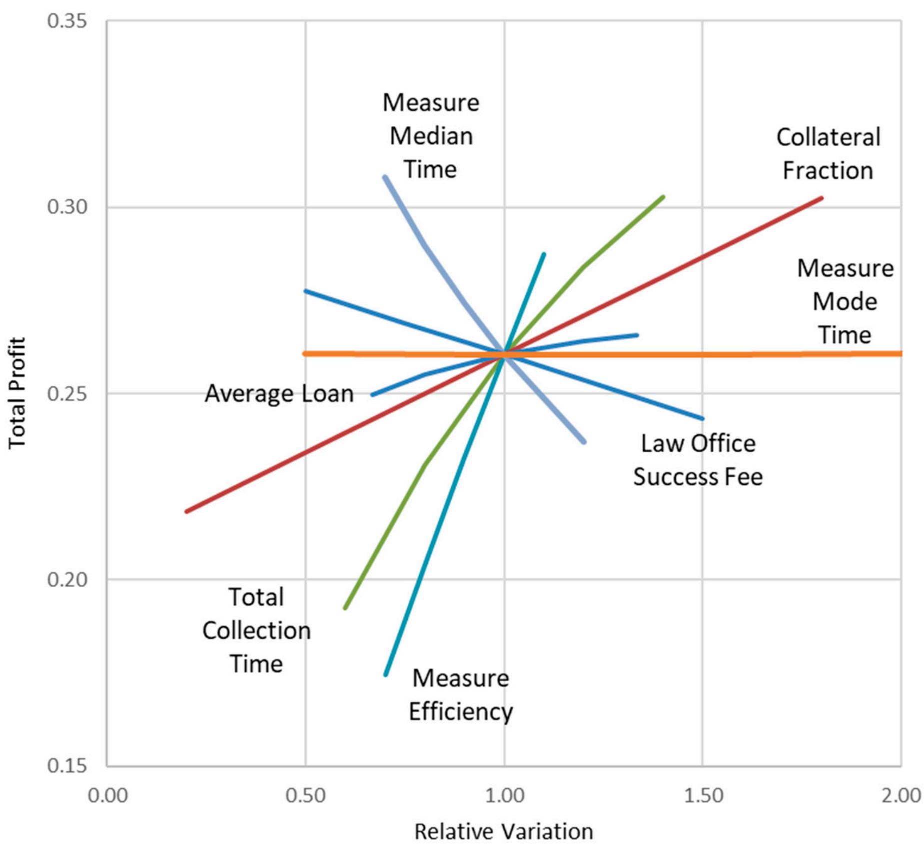
Cost Data

The "Law Office Success Fee" played a significant negative role in the total profit. Substantially, it allocated the profits between the NPL portfolio manager and the legal office. For this reason, this parameter is crucial for portfolios purchase agreements.

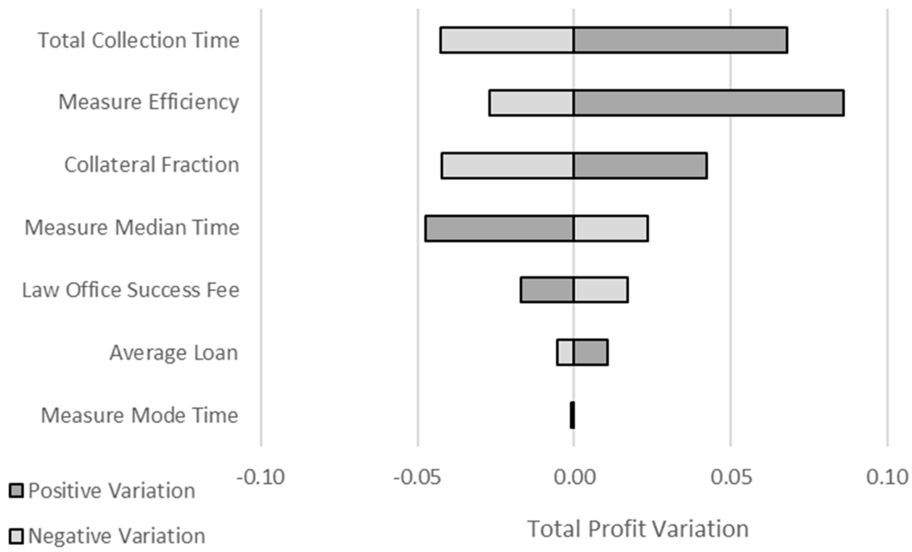
Collection Strategy

"Total Collection Time" had a significant positive effect, but it was constrained by the servicer's collection policy. Instead, the allocation of the total collection time into measures of differing duration was a topic of optimization.

Based on the above sensitivity analysis, it can be concluded that the profit ranged between 20% and 30%.



(**a**)



(**b**)

Figure 13. Sensitivity Analysis. (**a**) Spider plot (**b**) Tornado plot.

5. Conclusions

A simple mathematical model was proposed to simulate the collection process of NPL portfolios based on the debtors' response to several legal measures (phone calls, extrajudicial notices, court orders, and foreclosures). The data on the debtors' behavior was taken from Greece during both expansion and recession periods.

The proposed model was used to price NPL portfolios, which is a crucial point in portfolio transactions between the banks and NPL servicers. For an NPL portfolio of credit cards and medium-sized personal loans, recent Greek data on cost, and a 5-year collecting period equally allocated to each measure, a total profit of 26% of the initial debt could be obtained, considering this value as a typical price of the NPL portfolio.

The model was also used to predict recovery, cost, and future profit cash flows which could be discounted against time to obtain the Net Present Value of the portfolio.

In addition, the collection efficiency could be increased using a better allocation of total time to measures. This could be an advantage for law offices with a collection recording system, who could update the parameters by periodically fitting the model to recorded data.

A sensitivity analysis was conducted to reveal the most significant factors affecting the collection process. The total collection time, the measure efficiency, and the portion of the loans with collateral proved to be the most significant factors affecting the results of the collection process.

In conclusion, the proposed method proved effective in: (a) pricing NPL portfolios, (b) predicting recovery, cost, and profit future cash flows, (c) optimizing recovery strategies, and (d) revealing the significant factors affecting the recovery process.

The innovation of this approach consisted of considering: (a) the effect of different legal measures on recovery separately, (b) the cost of legal actions, and (c) the time variable response of debtors.

The main contribution of this work is that it sheds light on the important question of NPL portfolio pricing, which is a crucial point for financial institutions concerning the NPL portfolios market.

Author Contributions: Conceptualization, A.Z.M., E.N.G. and Y.D.C.; Methodology, A.Z.M., E.N.G. and Y.D.C.; Software, A.Z.M.; Validation, A.Z.M.; Formal analysis, A.Z.M.; Data curation, A.Z.M. and E.N.G.; Writing—original draft, A.Z.M.; Writing—review & editing, E.N.G. and Y.D.C.; Supervision, Y.D.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data sharing not applicable.

Acknowledgments: We thank the reviewers for their valuable contribution.

Conflicts of Interest: The authors declare no conflict of interest.

References

Alihodžić, Almir, and İbrahim Halil Ekşï. 2018. Credit growth and non-performing loans: Evidence from turkey and some balkan countries. *Eastern Journal of European Studies* 9: 229–49.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis. 2016. Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics* 131: 1593–636. [CrossRef]

Beck, Roland, Petr Jakubik, and Anamaria Piloiu. 2015. Key determinants of non-performing loans: New evidence from a global sample. *Open Economies Review* 26: 525–50. [CrossRef]

Bellotti, Anthony, Damiano Brigo, Paolo Gambetti, and Frédéric Vrins. 2021. Forecasting recovery rates on non-performing loans with machine learning. *International Journal of Forecasting* 37: 428–44. [CrossRef]

Blanchard, Olivier, and Pedro Portugal. 2017. Boom, slump, sudden stops, recovery, and policy options. portugal and the euro. *Portuguese Economic Journal* 16: 149–68. [CrossRef]

Bloom, Nicholas. 2009. The Impact of Uncertainty Shocks. *Econometrica* 77: 623–85. [CrossRef]

Bolognesi, Enrica, Cristiana Compagno, Stefano Miani, and Roberto Tasca. 2020a. Non-performing loans and the cost of deleveraging: The italian experience. *Journal of Accounting and Public Policy* 39: 106786. [CrossRef]

Bolognesi, Enrica, Patrizia Stucchi, and Stefano Miani. 2020b. Are NPL-backed securities an investment opportunity? *Quarterly Review of Economics and Finance* 77: 327–39. [CrossRef]

Calabrese, Raffaella, and Michele Zenga. 2008. Measuring loan recovery rate: Methodology and empirical evidence. *Statistica e Applicazioni* 6: 193–214.

Campello, Murillo, Gustavo S. Cortes, Fabrício d'Almeida, and Gaurav Kankanhalli. 2022. Exporting Uncertainty: The Impact of Brexit on Corporate America. *Journal of Financial and Quantitative Analysis* 57: 3178–22. [CrossRef]

Carleo, Alessandra, Roberto Rocci, and Maria Sole Staffa. 2023. Measuring the recovery performance of a portfolio of NPLs. *Computation* 11: 29. [CrossRef]

Carpinelli, Luisa, Giuseppe Cascarino, Silvia Giacomelli, and Valerio Vacca. 2017. The management of non-performing loans: A survey among the main italian banks. *Politica Economica* 33: 157–87. [CrossRef]

Chaibi, Hasna, and Zied Ftiti. 2015. Credit risk determinants: Evidence from a cross-country study. *Research in International Business and Finance* 33: 1–16. [CrossRef]

Chamboko, Richard, and Jorge M. Bravo. 2016. On the modelling of prognosis from delinquency to normal performance on retail consumer loans. *Risk Management* 18: 264–87. [CrossRef]

Cortes, Gustavo S., George P. Gao, Felipe B. G. Silva, and Zhaogang Song. 2022. Unconventional Monetary Policy and Disaster Risk: Evidence from the Subprime and COVID–19 Crises. *Journal of International Money and Finance* 122: 102543. [CrossRef]

Dantas, Manuela M., Kenneth J. Merkley, and Felipe B. G. Silva. 2023. Government Guarantees and Banks' Income Smoothing. *Journal of Financial Services Research* 63: 123–73. [CrossRef]

Dimitrios, Anastasiou, Louri Helen, and Tsionas Mike. 2016. Determinants of non-performing loans: Evidence from euro-area countries. *Finance Research Letters* 18: 116–19. [CrossRef]

Foglia, Matteo. 2022. Non-Performing Loans and Macroeconomics Factor: The Italian Case. *Risks* 10: 21. [CrossRef]

Ghosh, Amit. 2015. Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability* 20: 93–104. [CrossRef]

Girardone, Claudia, Philip Molyneux, and Edward P. M. Gardener. 2004. Analysing the determinants of bank efficiency: The case of italian banks. *Applied Economics* 36: 215–27. [CrossRef]

Karadima, Maria, and Helen Louri. 2020. Non-performing loans in the euro area: Does bank market power matter? *International Review of Financial Analysis* 72: 101593. [CrossRef]

Karadima, Maria, and Helen Louri. 2021. *Determinants of Non-Performing Loans in Greece: The Intricate Role of Fiscal Expansion*. GreeSE Paper No. 160. London: Hellenic Observatory, LSE.

Khairi, Ardhi, Bahri Bahri, and Bhenu Artha. 2021. A Literature Review of Non-Performing Loan. *Journal of Business and Management Review* 2: 366–73. [CrossRef]

Konstantakis, Konstantinos N., Panayotis G. Michaelides, and Angelos T. Vouldis. 2016. Non-performing loans (NPLs) in a crisis economy: Long-run equilibrium analysis with a real time VEC model for Greece (2001–2015). *Physica A: Statistical Mechanics and Its Applications* 451: 149–61. [CrossRef]

Li, Geng, Muzi Chen, and Xiaoguang Yang. 2022. Impact of centralized management on recovery rates of credit loans. Paper presented at the Chinese Control Conference, CCC, Hefei, China, July 25–27; pp. 7497–502. [CrossRef]

Louzis, Dimitrios P., Angelos T. Vouldis, and Vasilios L. Metaxas. 2012. Macroeconomic and bank-specific determinants of non-performing loans in greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking and Finance* 36: 1012–27. [CrossRef]

Makri, Vasiliki, Athanasios Tsagkanos, and Athanasios Bellas. 2014. Determinants of non-performing loans: The case of eurozone. *Panoeconomicus* 61: 193–206. [CrossRef]

Manz, Florian, Birgit Müller, and Dirk Schiereck. 2020. The pricing of European non-performing real estate loan portfolios: Evidence on stock market evaluation of complex asset sales. *Journal of Business Economics* 90: 1087–120. [CrossRef]

Marouli, A. Z., Yannis. D. Caloghirou, and Eugenia. N. Giannini. 2015. Non-performing debt recovery: Effects of the greek crisis. *International Journal of Banking, Accounting and Finance* 6: 21–36. [CrossRef]

Messai, Ahlem Selma, and Fathi Jouini. 2013. Micro and macro determinants of non-performing loans. *International Journal of Economics and Financial Issues* 3: 852–60.

Nikolaidou, Eftychia, and Sofoklis D. Vogiazas. 2014. Credit risk determinants for the bulgarian banking system. *International Advances in Economic Research* 20: 87–102. [CrossRef]

Nikolaidou, Eftychia, and Sofoklis Vogiazas. 2017. Credit risk determinants in sub-saharan banking systems: Evidence from five countries and lessons learnt from central east and south east european countries. *Review of Development Finance* 7: 52–63. [CrossRef]

Orlando, Giuseppe, and Roberta Pelosi. 2020. Non-performing loans for italian companies: When time matters. an empirical research on estimating probability to default and loss given default. *International Journal of Financial Studies* 8: 68. [CrossRef]

Perotti, Enrico C. 1993. Bank lending in transition economies. *Journal of Banking and Finance* 17: 1021–32. [CrossRef]

Saulītis, Andris. 2023. Nudging debtors with non-performing loans: Evidence from three field experiments. *Journal of Behavioral and Experimental Finance* 37: 100776. [CrossRef]

Scardovi, Claudio. 2015. *Holistic Active Management of Non-Performing Loans*. Berlin/Heidelberg: Springer, pp. 1–153. [CrossRef]

Stijepović, Ristan. 2014. Recovery and reduction of non-performing loans-podgorica approach. *Journal of Central Banking Theory and Practice* 3: 101–18. [CrossRef]

Tupayachi, Jose, and Luciano Silva. 2022. Better Efficiency on Non-performing Loans Debt Recovery and Portfolio Valuation Using Machine Learning Techniques. In *Production and Operations Management*. Edited by Jorge Vargas Florez, Irineu de Brito Junior, Adriana Leiras, Sandro Alberto Paz Collado, Miguel Domingo González Alvarez, Carlos Alberto González-Calderón, Sebastian Villa Betancur, Michelle Rodriguez and Diana Ramirez-Rios. Springer Proceedings in Mathematics & Statistics. Cham: Springer, vol. 391. [CrossRef]

Wang, Siyi, Xing Yan, Bangqi Zheng, Hu Wang, Wangli Xu, Nanbo Peng, and Qi Wu. 2021. Risk and return prediction for pricing portfolios of non-performing consumer credit. Paper presented at the ICAIF 2021—2nd ACM International Conference on AI in Finance, Virtual Event, November 3–5.

Ye, Hui, and Anthony Bellotti. 2019. Modelling recovery rates for non-performing loans. *Risks* 7: 19. [CrossRef]