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Integrating Customer Portfolio Theory and the Multiple Sources of Risk Approaches to Model Risk-Adjusted Revenue

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Abstract: This study proposes new methods to formulate customers' risk-adjusted revenue (RAR) metrics applied to the financial industry. Using a customer dataset provided by a loan company, we compute RAR using benchmark approaches presented in the literature and new formulas that combine the Customer Portfolio Theory and the Multiple Sources of Revenues approaches. We validate the efficiency and originality of our formulations by implementing statistical tests to check for differences across the different RAR measures. We find that the proposed RAR models are unique and can be implemented in the industry to account for multiple sources of risk, hence providing managers with ways to improve their valuation of customers' portfolios.

Keywords: Data-Driven Models, Analytics, Customer Valuation, Risk-Adjusted Revenue, Management

1. INTRODUCTION

Many studies have highlighted the importance of managing customers to ensure the firm's financial success (Gupta et al., 2004; Kumar and Reinartz, 2016; Srivastava et al., 1998). In fact, the optimal allocation of resources and the extension of customers' lifetime within a firm is directly related with the maximization of the company's profit (Gupta et al., 2004; Kumar and Reinartz, 2016; Srivastava et al., 1998). Recently, financial institutions have increased their investments in marketing-related activities worldwide. For example, Canadian banks have recently reported an average $2.5 million annual investment (FDIC, 2020). Thus, it is crucial to assess customer value before deciding on marketing resource allocation (e.g., retention or acquisition). In fact, a large literature explores different customer valuation metrics (Gupta et al., 2004; Kumar and Reinartz, 2016).

A literature review on customer valuation metrics shows the prevalence of studying Customer Lifetime Value (CLV) and Risk-Adjusted Revenue (RAR) applied to a variety of industry contexts (Gupta et al., 2004; Kumar and Reinartz, 2016; Tarasi et al., 2011; Homburg et al., 2009; Singh et al., 2013). More related to this paper, Risk-Adjusted Revenue (RAR) is a customer valuation metric that accounts for risk. Studies that model RAR can be grouped in two different streams: models that are based on the adapted Customer Portfolio Theory (CPT) (Buhl and Heinrich, 2008; Dhar and Glazer, 2003) and those that use the Multiple Sources of Risk (MSR) approach (Singh et al., 2013; Singh and Singh, 2016; Ryals and Knox, 2005). However, no research to date has proposed integrating these two methods.

This study aims to model RAR in the financial sector, more specifically in the loan industry. We implement benchmark models that follow CPT and MSR approaches (Singh et al., 2013; Singh and Singh, 2016; Ryals and Knox, 2005; Buhl and Heinrich, 2008; Dhar and Glazer, 2003). We also propose new RAR formulations that integrate these two approaches, hence extending the existing models presented in the literature. In particular, we focus on exploring the uniqueness and applicability of the new RAR metrics compared to the benchmark methods. This problem was motivated by the industry's constant need to increase the accuracy of customer valuation measurement and prediction. The methods proposed in this study provide managers with efficient new ways to predict individual customer valuations and to define customers' portfolios that support efficient allocation of marketing resources for customer retention and acquisition.

The rest of the paper is organized as follows. Section 2 presents a literature review. Section 3 discusses the methods used in this paper. Section 4 presents the obtained results. finally, Section 5 concludes and discusses future research avenues.

2. LITERATURE REVIEW

Customer risk can be defined differently depending on the industry and specific business characteristics. As a consequence, various definitions of risk are presented in the literature. For instance, in the financial (contractual)

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setting, Kumar and Reinartz (2012) define customer risk as the variability of income provided by a customer. Singh et al. (2013) add to this definition customers' Probability of Default (PD) in the context of the credit card industry since it incorporates both the variability and disruption of payments. In a non-contractual retail setting, another customer risk definition is given by Martínez et al. (2018) who consider risk as the probability that a customer stops purchasing products or services for a certain period of time. In the telecommunication industry (contractual setting), Verbeke et al. (2012) consider customers' likelihood of churn as customer risk. Regardless of how risk is measured, these studies agree on the concept that customer risk incorporates the possibility that a customer's relationship with the firm does not reach the level expected by the company. Therefore, the better a business can understand and assess a customer's specific risk, the better it can manage that risk to achieve the wished results (e.g., sales, cash flows, and returns) (Kumar and Reinartz, 2012).

RAR is a customer valuation metric that accounts for risk (Singh et al., 2013; Dhar and Glazer, 2003; Tarasi et al., 2011). Its use is recommended when a correlation between risk and return is positive, meaning that the riskiest customers are also the most profitable (Singh et al., 2013). Most studies that model RAR rely on the CPT. In this literature, only one measure of risk (β) and one return indicator (usually customers' cash flow) are used to define RAR (Buhl and Heinrich, 2008; Dhar and Glazer, 2003; Tarasi et al., 2011). Another approach to assess RAR considers MSR, which is determined by relevant risk factors associated with the industry and business setting (Singh et al., 2013; Ryals and Knox, 2005; Homburg et al., 2009). Examples of different sources of risk used when assessing RAR through this perspective include customers' PD (Singh et al., 2013) and churn (Ryals, 2010).

RAR models that are derived from the CPT target customers in different groups based on a single source of return (usually cash flow) and one source of risk (volatility of income (β)). Dhar and Glazer (2003) is the first study to use CPT to model RAR. They classify Business-to-Business (B2B) customers into two segments based on their industry and location. Then, they explore these segments' values under a risk/return perspective, where the return is generated by income from different sources, and risk (β) is the volatility of customers' return. Tarasi et al. (2011) also uses a similar approach to model RAR and apply it to a B2B dataset. However, they cluster customers into seven different groups based on their average income. These studies cluster customers into portfolios (assets) and then apply the CPT, considering their respective risk and return relations. By implementing CPT analysis, the most efficient customers are identified, and all other customers' (portfolio) values can be assessed by comparison.

RAR models that consider MSR explore variables related to various revenue streams generated by customers. These variables depend on the nature of each business. For example, Singh et al. (2013) consider as sources of earning the interchange, fee, and interest income, while the sources of risk include the volatility of each earning stream, β, and the customers' Probability of Default (PD). In their study, Singh et al. (2013) propose a Data Envelopment Analysis (DEA) method to model RAR in which the inputs are the sources of risk, and the outputs are the sources of income. Other studies later extend this model to include the Recency, Frequency, and Monetary (RFM) variables in the DEA model. In particular, Singh and Singh (2016) obtain an efficiency indicator for each customer that accounts for returns from different sources of income and for multiple sources of risk such as the probability of churn, the likelihood of reaching a minimum amount of sales, and the volatility of customer purchases. Using a different modeling approach, Ryals and Knox (2005) account for the customers' specific insurance claims and the volatility of their revenue streams. Also, Ryals (2010) studies RAR in the insurance industry and includes as metrics of risk the probability of churn and the volatility of cash flow. Finally, Homburg et al. (2009) consider the risks of customers switching segments by up/downgrading their credit score and their likelihood of churn as sources of uncertainty.

2.1 RAR Formulation

Similar to other customer valuation metrics, RAR is formulated using information about customers' cash flow which accounts for all sources of profits a customer might provide to a firm in a given period of time. Equation 1 presents the general formula to compute RAR. It is important to highlight that the RAR models presented in the literature differ on the method used to calculate the discounting rate, (i).

$$RAR = \sum_{t=0}^{T} \frac{\delta}{(1+i)^t}, \tag{1}$$

where RAR is the risk-adjusted revenue, t and T are a counter and the maximum period of time observed for each customer, respectively, δ is the net profit revenue (income), and i is the discounting rate.

Table 1 summarizes the most recent RAR formulations proposed in the literature grouped by CPT and MSR approaches. Ryals (2002) & Ryals and Knox (2005) discounting rate formulation does not depend on the β risk, similar to Dhar and Glazer (2003) and Buhl and Heinrich (2008) studies. However, in their proposed approach, the factor of risk considered is given by R_c and R_m, the credit rating classification for the customer and market, respectively. Thus, although all studies reviewed in the literature defined the discounting rate considering a specific factor of risk (for CPT models) or multiple sources of risk (MSR approach), they aim to correctly assess customers' level of risk then compute their value.

3. METHODOLOGY

3.1 Dataset and Experimental Setup

Our experiments use real-world data from one of the largest online lending marketplaces in the US. The Lending Club's dataset is available at the company's website (LendingClub Corporation, 2019) and a data science competition platform (Kaggle, 2019). It contains financial, text-based, behavioral, and demographic features, summing up 75 variables. Some features in the dataset are loan status, funded amount, latest payment information, interest rate,

Table 1. An overview of different methods and parameters to calculate the discounting rate in RAR models.

Study	**Formulas used**	**Description**
Approaches for calculating the discounting rate (CPT models)		
Ryals (2002) & Ryals and Knox (2005)	$i = \frac{WACC \times R_c}{R_m}$	Two different criteria are used: R_c/R_m (risk of customer and market) and Weighted Average Cost of Capital (WACC). Customer risk is defined as the weighted customer credit rating for individual customers and its average for the entire portfolio representing the market risk.
Dhar and Glazer (2003)	$i = \psi_m \times \beta$	β is the systematic risk, defined as $\beta = cov(\varphi_{ct}, \varphi_{mt})/var(\varphi_{mt})$, where φ_{ct} and φ_{mt} are the return for customer c and market m at each period of time t. ψ_m represents the expected rate of return of the market, which can be defined as the average of customers' spread given by $((rate+1)/(CDI+1))^{12}$, where $rate$ is the customer interest rate and CDI is the annual average of the USA certificate of interbank deposits (Brock and Suarez, 2000; Angbazo et al., 1998).
Buhl and Heinrich (2008)	$i = \psi_f + \beta(\psi_m - \psi_f)$	An application of the CAPM model is proposed: β and ψ_m follow the same definition given by Dhar and Glazer (2003). ψ_f is the minimum expected rate of return (minimum spread of the portfolio), which correspond to the customer (asset) with the lowest risk ("risk free").
β and volatility definitions commonly used in RAR (MSR models)		
Singh et al. (2013), Tarasi et al. (2011), Hopkinson and Lum (2002)	$\beta = cov(\varphi_{ct}, \varphi_{mt})/var(\varphi_{mt})$ $\sigma = \sqrt{E(X^2) - (E(X))^2}$	Singh et al. (2013) use risk as part of the multiple input/output approach implemented in their DEA model. In all studies, β is calculated as the ratio covariance/variance of all sources of income available (for customers and market). Also, σ refers to the volatility (standard deviation) in each source of income over time, where $E(X)$ is the expected (average) value of X.

and customer credit rating. The latter is a categorical variable with seven classes– from A (lowest) to G (highest)– describing customers' credit risk level.

The experiments are selected to estimate the RAR of each customer in the dataset and also to measure RAR for each portfolio of customers (e.g., grouped by their credit rating class). To achieve our objectives, first, we extract different sources of risk and return from the dataset, then the examples are pre-processed, and feature engineering is performed. The baseline models are implemented along with the proposed RAR models. Finally, the results are measured and compared using statistical tests to assess the originality of the proposed models (Dietterich, 1998).

3.2 Data Pre-processing Treatment (DPT)

The DPT tasks can be described into two steps. First, the dataset is cleaned from duplicated, text-based, and identification variables. Dummies replace the nominal features by implementing an ordinal encoder (two possible values) or one hot encoder (more than two values), depending on the number of possible classes in each nominal feature. Second, missing values, outliers, correlation, and multicollinearity are handled. The missing values are treated based on their frequency across features. If the missing values for a given feature represent more than 5% of the examples, nothing is done. In all other cases, the missing values are replaced by either the mode, mean, or median value of each feature. The outliers are evaluated with the creation of dummies to analyze their behavior, in order to determine their importance to the model. Correlation and multicollinearity are tested by measuring the variance inflation factor. We drop features from the dataset if we find a pair of variables with multicollinearity or correlation over 90%. A gain of 60% of features is observed over the initial dataset (75 features) after the DPT tasks.

3.3 RAR Estimation, Parameter Settings and Evaluation Criteria

Table 1 lists three groups of studies that differ in how RAR is assessed, specifically in the way the discounting rate is computed. This paper uses these three baseline approaches, and proposes various extensions for each.

Table 2 presents the first baseline model (Case 1) and three proposed extensions (Cases 1.a, 1.b, and 1.c). Case 1 computes the discounting rate according to the CPT approach and uses the customer credit rating as a risk variable (see Table 2). The proposed extended models consider four sources of risk: 1. The recency of delinquency [1], 2. The volatility of different sources of income, installments, and fees (the Standard Deviation (SD) of each stream of return), 3. The credit rating, which is handled using the Weight on Evidence (WOE), and the normalized average of interest rate per segment (credit rating grade) (Abdou, 2009; Linkov et al., 2011; Sbrana, 2012), and 4. The PD. Thus, instead of using the customer credit rating risk (R_C) and the market (portfolio) risk (R_M), in Case 1's extensions, we define ρ_c and ρ_m as the customer and market (portfolio) risk, respectively, with three possible variations for ρ_c using different approaches (Table 2).

Note that Case 1.a is modeled using ρ_c as the output of a PD model. The PD is estimated using a Logistic Regression (LOGIT) model, where the four sources of risk are the independent variables. We run two different LOGIT models because the credit rating (one of the sources of risk) is encoded using different methods (WOE and the normalized average of interest rate). Also, we consider three different Lending Club's WACC: 6.45%, 7.26%, and 8.71% (Investors, 2020). These annual percentages are the minimum, average and maximum WACC of the Lending Club, for the time frame of our dataset (2005–2017). In Case 1.b,

[1] The recency variable was initially presented in months and later normalized during DPT.

ρ_c is computed through a weighted average formula. The weights are the transformed coefficients ($exp(\theta)$) from the LOGIT models implemented in Case 1.a (Borooah, 2002). This is because, on average, the relative importance of each source of risk has a different impact on each customer's RAR. In Case 1.c, ρ_c is defined as a simple average of the customer's risks, which are equally weighted. Given these different formulations, we obtain six labeled targets in each model: Cases 1, 1.a, 1.b, and 1.c.

The second and third baseline models, their extensions, and parameter settings are summarized in Table 2. These models relate to the RAR formulation based on the MSR models (see Table 1). The extensions proposed here explore different formulas for β, which is used in the discounting rate formulation of RAR. In the baseline models (Table 1), $\beta = cov(\varphi_{ct}, \varphi_{mt})/var(\varphi_{mt})$, where φ_{mt} and φ_{ct} are the total return for market m and customer c at each period t, respectively. In the extended cases, two different variations are considered instead of calculating β for the total return—the first only accounts for installments and the second only for the fees paid by customers. The expected return of the market, or in our case portfolio (ψ_m), and the minimum return (ψ_f) are derived from the spread calculation $\psi_m = ((rate + 1)(CDI + 1))^{12}$, where $rate$ is the average of the customer's loan interest rate, and Interbank Deposit Certificate (CDI) corresponds to the annual average of the US certificates of interbank deposits for the same period as our dataset (2007–2015). Spread is a metric commonly used in the finance literature to measure customers' expected rate of return (Brock and Suarez, 2000; Angbazo et al., 1998). Thus, for each baseline model in Cases 2 and 3, two extensions are proposed (2.a, 2.b, and 3.a, 3.b). The details are presented in Table 2 and complementary descriptions for each labeled RAR are provided in the Appendix A.1.

The RAR assessment is evaluated through the implementation of t-tests to compare the statistical difference between all baseline and extended labeled RARs (Tables 1 and 2). The t-test results indicate whether the extended models offer an original method to assess customers' RAR. This information is extracted and used to compare and discuss the obtained results in this research.

4. RESULTS

4.1 RAR baseline models

Figures 1 and 2 show the average discounting rate grouped by the credit rating classification provided by the company's dataset as well as the RAR for each of these baseline models. Further, only four out of the six benchmark models' discounting rates and RAR are shown: baseline Case 2 and 3, and two of the baseline Case 1 model. These cases use the average WACC but differ in the method to encode the credit rating (WOE and the normalized average of interest rate). These labels were selected to facilitate visualization and to demonstrate various scenarios. Values for the discounting rate are presented in (%), and the RAR values are normalized.

In Figure 1, we can observe that for both Case 2 and 3, there is only a small disparity between the discounting rate and ratings of credit. The curves are more constant

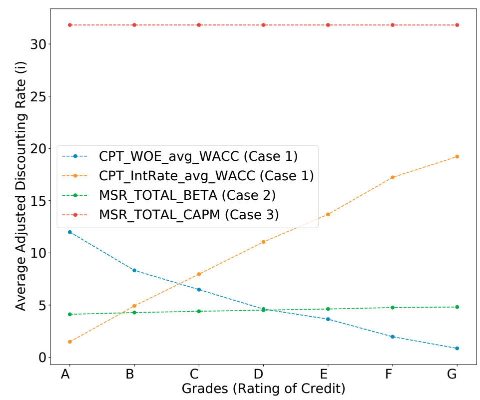

Fig. 1. Results for different baseline models' discounting rates: CPT_WOE_avg_WACC (Case 1, encoded with WOE), CPT_IntRate_avg_WACC (Case 1, encoded with the normalized average interest rate), MSR_TOTAL_BETA (Case 2) and MSR_TOTAL_CAPM (Case 3).

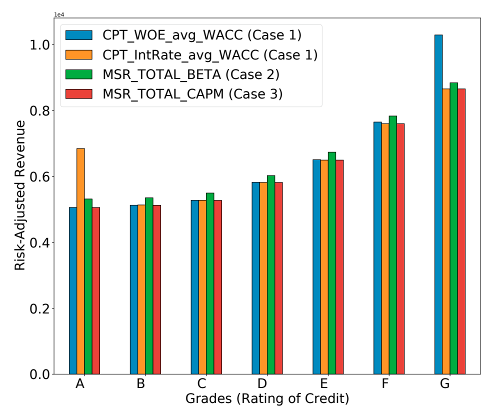

Fig. 2. Results for different baseline RAR models: CPT_WOE_avg_WACC (Case 1, encoded with WOE), CPT_IntRate_avg_WACC (Case 1, encoded with the normalized average of interest rate), MSR_TOTAL_BETA (Case 2) and MSR_TOTAL_CAPM (Case 3).

across credit rating classes on these cases because their discounting rate formulation only accounts for beta risk, not for the customers' credit rating. However, in Case 1, an inverse relationship between discounting rate and credit rating can be seen. For instance, using the average interest rate method increases the discounting rate as the credit rating decreases. Considering the WOE method, the discounting rate decreases with lower customer credit rating.

4.2 PD estimation (LOGIT)

Case 1's extensions, which use a PD model, are designed by implementing LOGIT models. Figure 3 presents the correlation matrix, which shows that there is no correlation among all independent variables (and target), except for the credit rating with WOE and with the normalized average interest rate. However, they are independent variables in different LOGIT models. It is important to

Table 2. Proposed RAR models.

Baseline model	Extensions	Description
Case 1. $i = \frac{WACC \times \rho_c}{\rho_m}$	Case 1.a. $\rho_c = \frac{1}{1+exp^{\ (\theta_0+\theta_1\chi_1+\ldots+\theta_4\chi_4)}}$; $\rho_m = \frac{\sum_{\eta=1}^{\eta}\rho_c}{\eta}$	First proposed extension (Case 1.a).
	Cases 1.b. and 1.c. $\rho_c = \frac{\sum_{\chi=1}^{4} w_\chi \chi_\chi}{\sum_{\chi=1}^{4} w_\chi}$; $\rho_m = \frac{\sum_{\eta=1}^{\eta}\rho_c}{\eta}$	Case 1.b and 1.c's extensions, which differ in the weight attribution. Case 1.b considers the transformed coefficients from the LOGIT regression built in Case 1.a, while Case 1.c considers an equally weighted average of all sources of risk. The market risk (ρ_m) is given by the average of each class of risk calculated in each case.
Case 2. $i = \psi_m \times \beta$	Case 2.a. $i = \psi_m \times \beta_p$	β is calculated over the principal (installment).
	Case 2.b. $i = \psi_m \times \beta_f$	β is calculated over the fees.
Case 3. $i = \psi_f + \beta(\psi_m - \psi_f)$	Case 3.a. $i = \psi_f + \beta_p(\psi_m - \psi_f)$	β is calculated over the principal (installment).
	Case 3.b. $i = \psi_f + \beta_f(\psi_m - \psi_f)$	β is calculated over the fees.

recall that these LOGIT models only differ in the method used to encode the credit rating, a categorical feature used as an independent variable. One LOGIT model uses the credit rating encoded with the WOE method, and another one considers the normalized average of interest rate grouped by rating. Both LOGIT models have an area under the curve of approximately 0.7. Given their similarity, we present the Receiver Operating Characteristic (ROC) curve that refers to the LOGIT using the WOE to encode the credit rating in Figure 4. Another extracted metric in both LOGIT models is accuracy, which about 94% in both cases.

Thus, below are the equations defining the LOGIT models used to discriminate the PD of each customer, according to the two different groups of independent variables used in these models:

$$PD_{woe} = \frac{\exp(-1.55 - 0.42\chi_1 - 0.07\chi_2 + 6.77\chi_3 - 3.21\chi_4)}{1 + \exp(-1.55 - 0.42\chi_1 - 0.07\chi_2 + 6.77\chi_3 - 3.21\chi_4)}, \quad (2)$$

$$PD_{int\_rate} = \frac{\exp(-3.94 - 0.39\chi_1 - 0.08\chi_2 + 6.77\chi_3 + 2.39\chi_4)}{1 + \exp(-3.94 - 0.39\chi_1 - 0.08\chi_2 + 6.77\chi_3 + 2.39\chi_4)}, \quad (3)$$

where χ_1 is the recency of the delinquency, χ_2 is the standard deviation of installments, χ_3 is the standard deviation of fees, and χ_4 is the sub-grade (credit rating), weighted using WOE in Equation 2 and the normalized interest rate by rating in Equation 3.

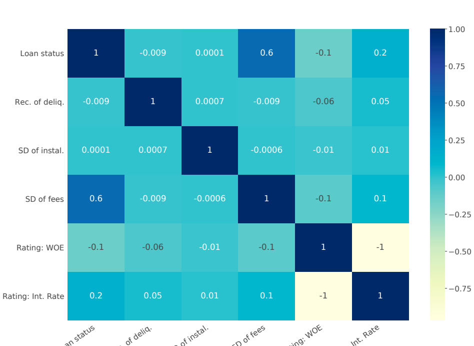

Fig. 3. Correlation matrix: independent and dependent variables used to model customers' PD.

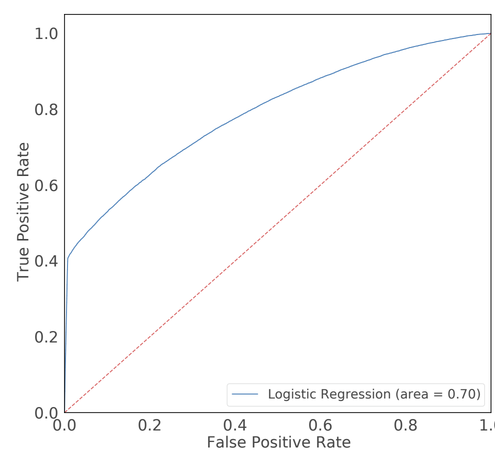

Fig. 4. ROC obtained on the customers' PD estimation.

4.3 RAR extended models

Similar computation results to the ones presented in Figures 1 and 2 (baseline models) are obtained for the extended models. For example, Figures 5–8 show the discounting rate and RAR for some of the extended approaches. Further, Figure 5 shows a similar ascending/descending behavior than the baseline models from which they are derived (Figure 1), hence demonstrating the robustness of the proposed models.

Figures 6 and 7 also demonstrate that there is a difference in the discounting rate behavior between the baseline and extended models for both Case 2 and 3. For instance, Figure 6 shows that the discounting rate for the baseline model Case 2 (MSR) increases as the credit rating decreases. However, when RAR is assessed considering only installment income and its variability (β), the discounting rate decreases as the credit rating of customers increases. Similar results are observed in the extensions of Case 3 (Figure 7). Figure 8 shows the RAR values for extensions on Case 1.a., however, for all the other labels, similar results are observed. Customers with a higher level of risk (rating G) are also the ones with higher RAR values.

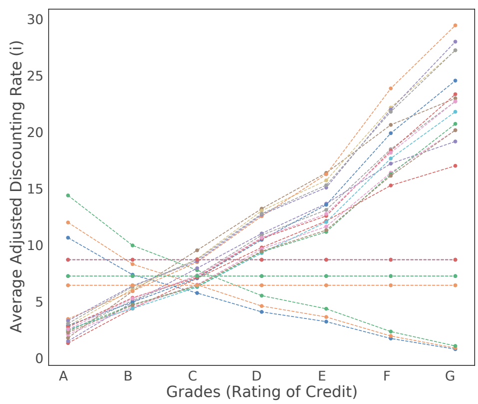

Fig. 5. Av. discounting rate: all variations of Case 1.

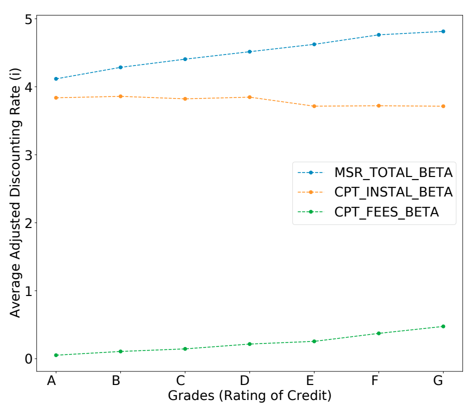

Fig. 6. Av. discounting rate: all variations of Case 2.

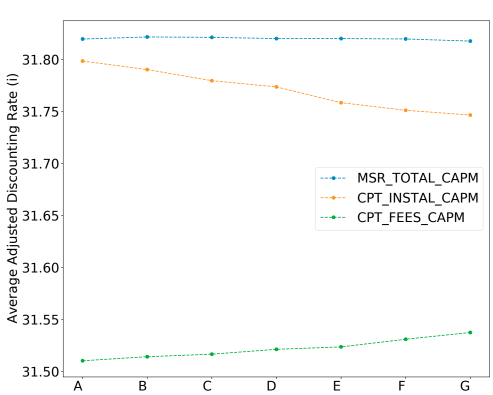

Fig. 7. Av. discounting rate: all variations on Case 3.

4.4 Discussion

Different remarks and comparisons can be made based on our results. First, the discounting rate and RAR computations in baseline models Case 2 and 3 (MSR_TOTAL_BETA,

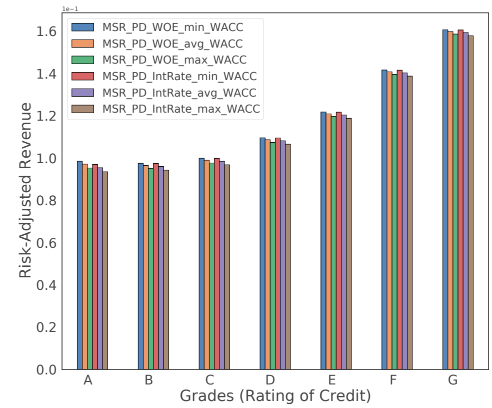

Fig. 8. Av. RAR: all variations on the Ext. Cases 1.a.

MSR_TOTAL_CAPM) and their extended versions (CPT_INSTAL_BETA, CPT_INSTALL_CAPM, CPT_FEES_BETA, and CPT_FEES_CAPM) do not include credit rating in formulating the discounting rate, and as a consequence, in their RARs (Tables 1 and 2). Thus, the average discounting rate (and RAR) for these cases is almost constant among all credit ratings (Figures 1, 5, 6, and 7). All the other models use credit rating as an input to calculate the discounting rate (and its RAR). This feature is encoded, as presented in Section 3.3, in two different ways: using the WOE method and the normalized average interest rate per credit rating class. The latter is implemented to impose an "opposite case" to the WOE method, as can be observed in Figures 1 and 5. Simultaneously, the discounting rate has a descending behavior when using the WOE method to encode the credit rating and an ascending behavior when using the normalized average interest rate. We choose the latter method to test some of the CPT concepts. Specifically, we verify whether the correlation between risk and return follows an inversely proportional relationship (Dhar and Glazer, 2003; Buhl and Heinrich, 2008; Tarasi et al., 2011). Figure 1 validates the CPT concepts; we can observe that rating A (lowest risk) and G (highest risk) have an average discounting rate of 1.2% and 19%, respectively.

Finally, the importance of using different sources of risk when modeling RAR has been presented in the literature by Singh et al. (2013), Singh and Singh (2016), Ryals and Knox (2005), and Homburg et al. (2009). Our study implements a LOGIT model that estimates the PD for the following sources of risk: recency of delinquency, volatility of sources of income, and credit rating. For the latter, since we use two separate approaches, we implement different LOGIT models. We obtain two sets of coefficients representing all extensions' variations to Case 1. Concerning the coefficients found in these LOGIT models, we can observe values greater than one (or smaller than -1) for the standard deviation of the fees and credit rating variables in both equations. This indicates that the odds ratios increase or decrease on a larger scale for these variables, meaning that PD prediction is affected more by these factors. Note that these models present an efficient PD estimation (Figure 4) and that the independent variables are not correlated or multi-collinear (Figure 3). Also, according to the correlation matrix, the credit ratings encoded differently are inversely correlated (correlation of -1.0), which is another supporting result for the behavior already observed in Figures 1 and 5. However, each LOGIT uses one of these independent variables; thus, they are not part of the same model.

5. CONCLUSIONS

In this study, metrics commonly used to model customers' Risk-Adjusted Revenue (RAR) either through the Customer Portfolio Theory (CPT) and Multiple Sources of Risk (MSR) were implemented, and new customer valuation metrics that arise from the integration of these methods were proposed. Coupling these methods to explore new computations of customers' valuation has not been applied in the literature, hence the novelty of this study. We integrated these approaches, implementing LOGIT models that accounted for multiple sources of customer risk, and scrutinized the sources of income a customer might provide to assess their value through products or services sources of income separately. Subsequently, the proposed models were compared with the benchmark approaches by performing statistical t-tests. Finally, we visualized discounting rate and RAR values across the baseline and extended models per customers credit rating classes (portfolios).

The results showed that the main concepts from the financial portfolio theory, which states that riskiest assets are also the most profitable, are observed in the baseline and extended RAR models. Also, the extended models provide original methods to assess customer value in the financial industry. Among all defined labels, there was no statistical evidence of equality between any of pairs of RARs considered in this study. Therefore, our findings validated the usage of these new RAR metrics to be widely applied in the industry. Among the different baseline and extended approaches, we suggest that managers select a RAR model based on the factors of risk and the information they have about their customers.

For future studies, exploring the different methods of portfolio definition through the use of machine learning models might provide a way to define customers' risk without including bias to the modeling process. Also, implementing predictive frameworks using either traditional statistical models (e.g., regressions) or machine learning algorithms would list the most important features when assessing customer value. This might provide managers with insights on the definition of pricing and marketing initiatives policies. Finally, our study can be applied to other datasets in the financial industry and any contractual settings in a business environment.

REFERENCES

Abdou, H. (2009). An evaluation of alternative scoring models in private banking. *Journal of Risk Finance*, 10, 38–53. doi:10.1108/15265940910924481.

Angbazo, L.A., Mei, J., and Saunders, A. (1998). Credit spreads in the market for highly leveraged transaction loans. *Journal of Banking & Finance*, 22(10), 1249–1282. doi:https://doi.org/10.1016/S0378-4266(98)00065-X.

Borooah, V. (2002). *Logit and Probit: Ordered and Multinomial Models*. Number (138) in Logit and probit: Ordered and multinomial models. SAGE Publications. URL `https://books.google.ca/books?id=H2mxYlRrcCoC`.

Brock, P.L. and Suarez, L.R. (2000). Understanding the behavior of bank spreads in latin america. *Journal of Development Economics*, 63(1), 113–134. doi:https://doi.org/10.1016/S0304-3878(00)00102-4.

Buhl, H. and Heinrich, B. (2008). Valuing customer portfolios under risk-return-aspects: A model-based approach and its application in the financial services industry. *Academy of Marketing Science review*, 12(5), 1–32. doi:10.5283/epub.23202.

Dhar, R. and Glazer, R. (2003). Hedging customers. *Harvard Business Review*, 81, 86–129.

Dietterich, T.G. (1998). Approximate statistical tests for comparing supervised classification learning algorithms. *Neural Comput.*, 10(7), 1895–1923. doi:10.1162/089976698300017197.

FDIC (2020). Federal Deposit Insurance Corporation - Statistics. URL `https://www.fdic.gov/bank/statistical/`.

Gupta, S., Lehmann, D.R., and Stuart, J.A. (2004). Valuing customers. *Journal of Marketing Research*, 41(1), 7–18. doi:10.1509/jmkr.41.1.7.25084.

Homburg, C., Steiner, V., and Totzek, D. (2009). Managing dynamics in a customer portfolio. *Journal of Marketing*, 73, 70–89. doi:10.1509/jmkg.73.5.70.

Hopkinson, G. and Lum, C. (2002). Valuing customer relationships: Using the capital asset pricing model (capm) to incorporate relationship risk. *Journal of Targeting, Measurement and Analysis for Marketing*, 10, 220–232. doi:10.1057/palgrave.jt.5740048.

Investors, F. (2020). Finbox - a toolbox for investors (wacc: models and historical data). URL `https://finbox.com/NYSE:LC/explorer/wacc`.

Kaggle (2019). Kaggle. URL `https://www.kaggle.com/`.

Kumar, V. and Reinartz, W. (2012). *Customer Relationship Management: Concept, Strategy, and Tools*. Springer Berlin Heidelberg, Berlim, 2 edition.

Kumar, V. and Reinartz, W. (2016). Creating enduring customer value. *Journal of Marketing*, 80(6), 36–68. doi:10.1509/jm.15.0414.

LendingClub Corporation (2019). Dataset. URL `https://www.lendingclub.com/info/statistics.action`.

Linkov, I., Welle, P., Loney, D., Tkachuk, A., Canis, L., Kim, J.B., and Bridges, T. (2011). Use of multicriteria decision analysis to support weight of evidence evaluation. *Risk Analysis*, 31(8), 1211–1225. doi:10.1111/j.1539-6924.2011.01585.x.

Martínez, A., Schmuck, C., Pereverzyev, S., Pirker, C., and Haltmeier, M. (2018). A machine learning framework for customer purchase prediction in the non-contractual setting. *European Journal of Operational Research*, 10, 1–9. doi:10.1016/j.ejor.2018.04.034.

Ryals, L. (2002). Measuring risk and returns in the customer portfolio. *Journal of Database Marketing & Customer Strategy Management*, 9(3), 219–227.

Ryals, L. (2010). Making customers pay: Measuring and managing customer risk and returns. *Journal of Strategic Marketing*, 11, 165–175. doi:10.1080/0965254032000133476.

Appendix A. RAR LABELS: BASELINE AND EXTENDED MODELS' DESCRIPTION

Table A.1. Feature selection and description of baseline and extended RAR labels.

Group of models and required features	Modeled label	Description
Baseline Case 1: Lending Club's WACC, Customer credit risk (Rating), Credit risk of the portfolio (average rating)	CPT_WOE_min_WACC	Encoding rating with WOE method using minimum WACC.
	CPT_WOE_avg_WACC	Encoding rating with WOE method using average WACC.
	CPT_WOE_max_WACC	Encoding rating with WOE method using maximum WACC.
	CPT_IntRate_min_WACC	Encoding rating with the weighted average of the normalized interest rate method and using minimum WACC.
	CPT_IntRate_avg_WACC	Encoding rating with the weighted average of the normalized interest rate method and using average WACC.
	CPT_IntRate_max_WACC	Encoding rating with the weighted average of the normalized interest rate method and using maximum WACC.
Baseline Case 2 and 3 and extensions (Cases 2.a/2.b and 3.a/3.b) : Volatility of customers return (installments and fees), the minimum and average of these returns, interest rate, and CDI (annual average of the USA certificates of interbank deposit).	MSR_TOTAL_BETA MSR_TOTAL_CAPM	Both baseline Cases 2 (MSR_TOTAL_BETA) and 3 (MSR_OTAL_CAPM) consider as return the total summed income from all sources (installments and fees).
	CPT_INSTAL_BETA	Only installments are included in returns.
	CPT_FEES_BETA	Only fees are included in returns.
	CPT_INSTAL_CAPM	Only installments are included in returns.
	CPT_FEES_CAPM	Only fees are included in returns.
Extensions of Case 1 (Case 1.a/1.b/1.c): All sources of risk (recency of delinquency, volatility, and rating), PD built using sources of risk and its transformed coefficients and, Lending Club's WACC	MSR_PD_WOE_min_WACC	PD model used the rating encoded with the WOE method and minimum WACC.
	MSR_PD_WOE_avg_WACC	PD model used the rating encoded with the WOE method and average WACC.
	MSR_PD_WOE_max_WACC	PD model used the rating encoded with the WOE method and maximum WACC.
	MSR_PD_IntRate_min_WACC	PD model used rating encoded with normalized average of interest rate method and minimum WACC.
	MSR_PD_IntRate_avg_WACC	PD model used rating encoded with normalized average of interest rate method and average WACC.
	MSR_PD_IntRate_max_WACC	PD model used rating encoded with normalized average of interest rate method and maximum WACC.
	MSR_PD_Coeff_WOE_min_WACC	Coefficients of the PD model used had the rating encoded with the WOE method and minimum WACC.
	MSR_PD_Coeff_WOE_avg_WACC	Coefficients of the PD model used had the rating encoded with the WOE method and average WACC.
	MSR_PD_Coeff_WOE_max_WACC	Coefficients of the PD model used had the rating encoded with the WOE method and maximum WACC.
	MSR_PD_Coeff_IntRate_min_WACC	Coefficients of the PD model used had the rating encoded with normalized average of interest rate method and minimum WACC.
	MSR_PD_Coeff_IntRate_avg_WACC	Coefficients of the PD model used had the rating encoded with normalized average of interest rate method and average WACC.
	MSR_PD_Coeff_IntRate_max_WACC	Coefficients of the PD model used had the rating encoded with normalized average of interest rate method and maximum WACC.
	MSR_WOE_min_WACC	Encoding rating with WOE method and minimum WACC.
	MSR_WOE_avg_WACC	Encoding rating with WOE method and average WACC.
	MSR_WOE_max_WACC	Encoding rating with WOE method and maximum WACC.
	MSR_IntRate_min_WACC	Encoding rating with the weighted average of the normalized interest rate method and minimum WACC.
	MSR_IntRate_avg_WACC	Encoding rating with the weighted average of the normalized interest rate method and average WACC.
	MSR_IntRate_max_WACC	Encoding rating with the weighted average of the normalized interest rate method and maximum WACC.