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Customer Valuation under Systematic and Idiosyncratic Risk: Evidence from a Private Bank in Brazil

Antonino de Andrade Machado[1] and André Nunes Maranhão[1]

Abstract

This study investigates how integrating finance-based measures of systematic and idiosyncratic risk into customer valuation deepens the understanding of client heterogeneity in private banking and enhances the managerial interpretation of financial performance. We hypothesize that decomposing and jointly analyzing both risk dimensions reveals interaction effects that materially influence Customer Lifetime Value (CLV) and aggregate Customer Equity (CE), providing a stronger analytical basis for service differentiation, pricing, and advisory efforts. Using a proprietary and rare longitudinal dataset of high-net-worth clients from a major Brazilian private bank, we reconstruct monthly margins, estimate volatility and beta relative to a benchmark, and project cash flows through deterministic and nonparametric methods. The results show that incorporating combined client-specific risk measures significantly alters CLV and CE relative to uniform discounting, improving balance and highlighting the managerial relevance of risk-based segmentation. The framework connects asset-pricing logic with service management, enabling more tailored, transparent, and financially grounded customer strategies.

JEL classification numbers: G21, L84, G12, C63.
Keywords: Financial Services, Private Banking, Customer Valuation, Risk-Adjusted Discounting, Systematic Risk, Idiosyncratic Risk, Customer Relationship Management.

[1] São Paulo School of Economics (EESP), Fundação Getulio Vargas (FGV), São Paulo, Brazil.

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1. Introduction

In financial services, the ability to quantify the economic value of client relationships is central to understanding long-term performance and portfolio stability. Customer Equity (CE) - the discounted value of the firm's customer base - provides a financial framework for linking relationship outcomes to measurable value. In private banking, where each client relationship involves substantial assets, personalized advisory, and exposure to financial risk, CE serves as a bridge between relationship management and asset valuation. Precise estimation of CE is therefore essential not only for pricing and resource allocation, but also for aligning service intensity and strategic decisions with clients' financial and behavioral profiles.

Private banking represents an especially demanding and insightful setting for customer valuation. Relationships with high-net-worth individuals (HNWIs) combine large financial stakes with elevated service expectations, sensitivity to pricing and quality, and pronounced heterogeneity in financial behavior and risk tolerance. Each client's portfolio composition, transaction intensity, and advisory needs contribute differently to profitability and exposure to financial risk. These characteristics make private banking both economically significant and theoretically relevant for understanding how value and risk interact in service-intensive financial relationships.

Despite its relevance, most applications of Customer Lifetime Value (CLV) and CE rely on uniform discount rates that implicitly assume identical risk exposure across clients. This simplification contrasts with asset-pricing principles, where the value of uncertain cash flows depends on their exposure to systematic (market-related) and idiosyncratic (client-specific) risk. As a result, existing models may fail to capture the true heterogeneity in financial risk that shapes the value and profitability of long-term client relationships.

Prior research has examined volatility and retention uncertainty in customer portfolios (e.g., Wangenheim and Lentz, 2005), but the joint incorporation of systematic and idiosyncratic risk into customer valuation remains underdeveloped - particularly in service-intensive financial environments such as private banking. By treating risk as both decomposable and measurable at the individual level, financial institutions can achieve greater precision in valuing clients and, consequently, in allocating resources and designing customized service strategies.

This study develops a risk-adjusted framework for Customer Equity that integrates two complementary dimensions of financial risk: (i) a systematic component, proxied by each client's beta relative to the overall portfolio benchmark, and (ii) an idiosyncratic component, represented by the volatility of client-level cash flows. Standard CLV models emerge as a special case when these risk factors are constant or null, maintaining tractability while introducing financial rigor to customer-based valuation.

The empirical analysis draws on a proprietary longitudinal dataset of approximately 1,000 high-net-worth individuals (HNWIs) served by a major private bank in Brazil. This segment, which manages over R$2.4 trillion in assets under management

(ANBIMA, 2025), is characterized by high heterogeneity, individualized service models, and strong sensitivity to financial markets. We reconstruct monthly contribution margins, estimate volatility and beta for each client, and project cash flows using deterministic and nonparametric techniques. Incorporating both risk dimensions materially alters CLV and CE estimates relative to conventional approaches, yielding more stable and interpretable valuations across forecast horizons and survival scenarios.

This research contributes along three dimensions. Conceptually, it embeds risk heterogeneity into the measurement of Customer Equity, aligning client valuation with asset-pricing theory and risk management principles. Empirically, it leverages a rare, high-frequency dataset to validate a risk-adjusted approach to customer valuation in a complex financial service setting. Managerially, it provides a replicable framework for refining pricing, resource allocation, and service customization in risk-sensitive client portfolios. Ultimately, it demonstrates that a deeper understanding of client value and behavior enhances the precision, accountability, and resilience of service management in financial institutions.

2. Literature Review

Customer Lifetime Value (CLV) and Customer Equity (CE) are foundational constructs linking customer-level profitability to firm-level financial performance. Blattberg and Deighton (1996) were among the first to articulate the logic of managing customers as financial assets, emphasizing that relationship drivers and service investments should be evaluated by their long-term contribution to customer value rather than short-term revenue. This shift reframed customer management from an operational function into a financial discipline centered on future cash flows.

Building on this foundation, Berger and Nasr (1998) and Blattberg, Getz, and Thomas (2001) formalized CLV as the net present value of expected future customer margins, while CE was defined as the aggregation of these values across the firm's customer base. Rust, Lemon, and Zeithaml (2004) linked CE to firm valuation and strategic decision-making, and Hogan et al. (2002) positioned CE management as a core element of marketing accountability. Gupta and Lehmann (2005) extended this financial perspective, showing how CE informs resource allocation and long-term value creation.

Subsequent studies incorporated behavioral and financial heterogeneity into these models. Gupta et al. (2006) introduced retention dynamics and probabilistic modeling, while Venkatesan and Kumar (2004) proposed a framework for customer selection and resource allocation based on CLV differentials. Wangenheim and Lentz (2005) advanced the use of financial risk measures - such as volatility and margin stability - for managing customer portfolios in financial services. Collectively, these works moved CE modeling toward more granular, data-driven representations of customer profitability.

Financial services, and particularly private banking, provide a natural setting where these dynamics become critical. Ekinci et al. (2014) developed a CLV model for banking that highlights how client heterogeneity, service intensity, and product mix affect profitability. Ryals (2008) underscored the strategic importance of viewing customers as assets, while Dhar and Glazer (2003) showed that managing customer portfolios can hedge firms against market uncertainty. Likewise, Kumar (2007) demonstrated how CE-based segmentation supports more efficient targeting, cross-selling, and retention initiatives in relationship-driven environments. Yet, despite the financial nature of these relationships, the explicit integration of asset-pricing logic into customer valuation remains limited.

The service-intensive nature of private banking further reinforces this need. Relationships are long-term, co-created, and highly sensitive to both financial and experiential performance. The value delivered depends not only on market outcomes but also on advisory quality, trust, and customization - all of which amplify heterogeneity in both cash flows and risk exposure. As Rust et al. (2004) note, in service contexts the customer relationship itself is a financial asset whose risk profile evolves over time, shaped by both market dynamics and relational stability. Therefore, accurate valuation requires frameworks capable of capturing this dual uncertainty.

Moreover, the effectiveness of relationship management and retention strategies plays a pivotal role in determining the persistence and volatility of cash flows. Private banking relies heavily on personalized service delivery, human expertise, and ongoing advisory interactions that influence client satisfaction and loyalty. These relational and operational investments - ranging from portfolio reviews to dedicated account management - represent substantial cost commitments whose returns are realized only through sustained relationships. Accordingly, measuring the financial contribution and risk-adjusted value of each client becomes essential for optimizing personnel allocation, service customization, and long-term portfolio profitability.

While risk-adjusted approaches to Customer Lifetime Value (RA-CLV) have been proposed, most applications treat risk as a uniform adjustment factor or a firm-level parameter rather than a customer-specific attribute. Although retention models have improved predictions of customer longevity (Fader, Hardie, and Lee 2007), discounting frameworks still seldom distinguish between systematic and idiosyncratic sources of uncertainty - factors that materially influence the present value of expected margins. This simplification limits the precision of customer valuation and, consequently, the accuracy of pricing and resource allocation decisions, particularly in private banking, where risk heterogeneity is both measurable and economically relevant.

The present study addresses this gap by proposing a tractable framework that integrates both idiosyncratic and systematic risk into the discounting process. Building on the financial and marketing foundations established by Blattberg and Deighton (1996), Rust et al. (2004), and Gupta et al. (2006), the model embeds risk-sensitive valuation directly at the client level. Conceptually, it aligns CE measurement with asset-pricing principles; empirically, it enhances the stability, comparability, and managerial usefulness of CE metrics in portfolios characterized by high-value, high-variance clients. The next section details the methodological structure and empirical setting used to operationalize this framework.

3. Methodology

We develop an empirical framework to assess client value in private banking through individualized, risk-adjusted discounting. The analysis relies on proprietary panel data from high-net-worth individuals (HNWIs) in Brazil and unfolds in three main steps. First, client-level contribution-margin series are preprocessed to address missing values, correct inconsistencies, and ensure sufficient continuity. Second, idiosyncratic and systematic risks are quantified using the volatility of individual margins and each client's beta relative to the portfolio benchmark, serving as a proxy for market sensitivity. Third, future cash flows are projected through deterministic and nonparametric methods and discounted with individualized rates that incorporate the estimated risk parameters.

To summarize the empirical design, Figure 1 illustrates the analytical pipeline comprising: (i) preprocessing of client-level contribution margins; (ii) estimation of idiosyncratic and systematic risk; and (iii) deterministic projections discounted by individualized rates. These steps yield client-level CLV estimates, which are aggregated to compute Customer Equity (CE). This structure enables a controlled comparison between uniform and risk-adjusted valuations, showing how heterogeneity in client exposure shapes long-term value and portfolio stability.

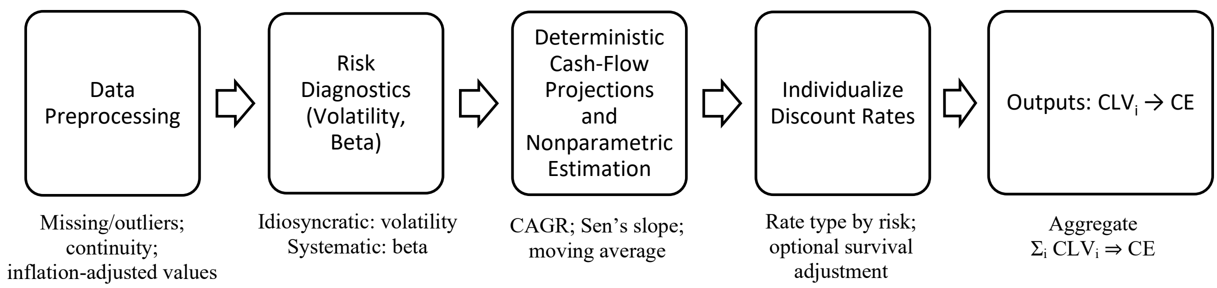

Figure 1: Pipeline for Risk-Adjusted Customer Equity Estimation

3.1 Data and Scope

We use proprietary, anonymized client-level data from the Private Banking division of a major Brazilian financial institution, encompassing clients randomly drawn from its national portfolio. The dataset spans December 2019 to December 2022 and initially comprised approximately 1,000 high-net-worth individuals (HNWIs). To ensure data integrity and continuity, we extracted the longest uninterrupted time window available and retained only clients actives in a specific period.

The key variable is the monthly contribution margin, expressed in local currency (Brazilian reais). This measure serves as a proxy for each client's financial return to the institution, implicitly capturing both revenues and related costs—such as service channels, advisory effort, and opportunity costs—without any inflationary or demographic adjustment, as directly observed in the dataset.

This configuration enables a consistent assessment of client-level financial performance, capturing heterogeneity in contribution and stability over time. By focusing on active and continuous relationships within a representative national sample, the dataset reflects the service-based nature of private banking, where sustained engagement and portfolio evolution drive long-term value creation.

3.2 Temporal Diagnostics and Risk Measures

The dataset is heterogeneous and high-dimensional, combining cross-sectional dispersion - clients with markedly different portfolio sizes and service intensities - with temporal variation in monthly contribution margins. Such diversity is intrinsic to private banking, where individualized advisory models and market exposure generate substantial heterogeneity in client performance. To ensure comparability and avoid distortions in risk estimation, we applied a consistent four-step preprocessing routine.

First, the monthly index between the first and last observation of each client was completed to maintain a continuous calendar, enabling comparable stationarity and trend tests (ADF, Jarque–Bera, Sen's slope). Second, missing or zero entries were forward-filled within client to prevent artificial volatility. Third, outliers were detected and corrected using the interquartile range (IQR) rule:

$$\begin{aligned}\text{Lower Bound} &= Q_1 - 1.5 \times \text{IQR}\\ \text{Upper Bound} &= Q_3 + 1.5 \times \text{IQR},\end{aligned} \tag{1}$$

where IQR represents the range between the first and third quartiles ($Q_3 - Q_1$), capturing the middle 50% of all observations. Values falling outside this range are considered atypical and replaced to preserve the underlying trend. This quartile-based correction is a simple and robust method for handling extreme values in heterogeneous datasets where distributions deviate from normality (Rousseeuw and Hubert, 2018). Fourth, we retained only clients with at least 24 consecutive monthly records after cleaning, resulting in a final sample of 949 active individuals.

The same IQR-based treatment was later applied vertically (across clients within

each month) when constructing the internal benchmark for beta estimation. A parallel log-based version of the pipeline was also executed to stabilize distributions and reduce sensitivity to extreme values. This combination of horizontal and vertical filtering accommodates both the cross-sectional and temporal dimensions of private-banking data.
We then compute two client-specific risk measures for use in the discounting process: an idiosyncratic risk proxy (volatility) and a systematic risk proxy (beta). Both are derived from the preprocessed monthly contribution-margin series and calculated in linear and logarithmic specifications.
For the log specification, monthly returns are defined as:

$$r_{i,t} = ln\left(mMargem_{i,t}\right) - ln\left(mMargem_{i,t-1}\right) \tag{2}$$

which symmetrically captures proportional changes and is additive across periods.

Idiosyncratic risk is defined as the mean absolute month-to-month change in returns:

$$v_{i,t} = \left| r_{i,t} - r_{i,t-1} \right| \tag{3}$$

capturing abrupt fluctuations regardless of direction.

Systematic risk is captured through a CAPM-inspired beta, estimated as the slope from an OLS regression of each client's returns on the benchmark constructed from the average return of all other active clients in the portfolio. This internal reference functions as a market proxy within the customer base and allows us to assess how each individual's performance co-moves with the collective behavior of the portfolio:

$$\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)} \tag{4}$$

where r_m is the monthly average return across all active clients in the portfolio.

Both linear and log versions of these measures are computed; the log transformation yields more stable distributions and reduces the influence of extreme values. Table 1 presents descriptive statistics.

Table 1: Statistics of risk measures (linear and log)

Metric	Mean	Std. deviation	Min	Max
Volatility (Linear)	0.087	0.052	0.010	0.412
Volatility (Log)	0.056	0.039	0.005	0.297
Beta (Linear)	0.88	0.61	-0.15	2.12
Beta (Log)	0.74	0.54	-0.18	1.98

Complementary diagnostics - including Augmented Dickey–Fuller (stationarity), Jarque–Bera (normality), and Sen's slope (trend) - indicate that most series are non-normal and exhibit significant trends, which motivates the robust projection strategies described in the next subsection.
Finally, we incorporate a constant monthly survival rate of $s = 0.60$ to illustrate how retention risk can be embedded into the valuation process. This value was chosen arbitrarily for analytical illustration, not as an empirically estimated parameter. Accordingly, the projected margin for each client i at time t is adjusted as:

$$F_{i,t}^{adj} = F_{i,t} \cdot s \tag{5}$$

where $F_{i,t}$ denotes the forecasted contribution margin. This adjustment introduces an illustrative retention effect into the CLV computation while preserving institutional confidentiality and allowing replication with alternative, data-driven survival assumptions. The resulting idiosyncratic and systematic risk measures provide the basis for constructing individualized discount rates in the following subsection.

3.3 Projection and Estimation of Future Cash Flows

The preprocessed contribution-margin series exhibit properties that limit the applicability of standard linear time-series models. Only 32.14% of the series are stationary according to the Augmented Dickey–Fuller (ADF) test, 81.03% reject normality in the Jarque–Bera test, and 84.74% present a significant negative trend under Sen's slope estimator. These diagnostics indicate instability, non-linearity, and pronounced heterogeneity across clients - patterns consistent with Dhar and Glazer (2003) and contrary to the stationarity assumptions often imposed in traditional Customer Lifetime Value (CLV) frameworks (Blattberg, Getz, and Thomas 2001; Rust, Lemon, and Zeithaml 2004; Ryals 2008).
Given these empirical characteristics, we employ robust deterministic methods to project future cash flows. This choice reflects the behavioral dynamics of private banking relationships, where margins evolve with client engagement, portfolio reallocation, and market sensitivity rather than following purely stochastic or stationary processes.

All projection methods incorporate a directional median correction, distinct from the IQR-based preprocessing described earlier. While the IQR rule detects and removes statistical outliers from observed data, the directional median correction ensures that projected series preserve the prevailing trajectory - using positive medians for clients with upward trends and negative medians for those with declining patterns. This adjustment maintains coherence with each client's historical behavior while mitigating residual distortions and enhancing comparability across projection models.

3.3.1 Average Monthly Growth Rate (AMGR)

The first deterministic projection method computes each client's average monthly growth rate based on observed percentage changes in contribution margin:

$$AMGR_{i,t} = \frac{M_{i,t} - M_{i,t-1}}{M_{i,t-1}} \tag{6}$$

where $M_{i,t}$ denotes the contribution margin of client i at month t.

This method provides a straightforward and transparent extrapolation of future margins, assuming that past average growth offers a reasonable baseline for near-term performance. The projection applies the mean observed rate across the historical period, without imposing distributional assumptions or parametric model constraints.

3.3.2 Compound Annual Growth Rate (CAGR)

The second projection method uses the monthly version of the compound annual growth rate (CAGR), which summarizes the cumulative change between the first and last valid observations of each client's series:

$$CAGR_i = \left(\frac{M_{final}}{M_{initial}}\right)^{\frac{1}{n}} - 1 \tag{7}$$

where n represents the number of months between the two observations.

CAGR condenses a client's long-term evolution into a single compounded rate, smoothing short-term fluctuations and reflecting sustained profitability over time. It serves as a stable and intuitive benchmark for forward-looking cash-flow projections.

3.3.3 Sen's Slope

The third deterministic method employs the Sen's slope estimator, a non-parametric technique widely applied in robust trend analysis (Kerketta and Singh, 2019). It calculates all pairwise slopes within each client's time series and takes their median as the overall trend estimate:

$$Slope_i = median\left(\frac{(M_t - M_s)}{(t-s)}\right), \forall\, s < t \tag{8}$$

By relying on medians rather than fitted coefficients, Sen's slope provides a robust alternative for heterogeneous datasets where normality and homoscedasticity cannot be assumed - conditions typical of private-banking customer margins.
Its resistance to transient shocks and local volatility makes it particularly suitable for identifying persistent long-term tendencies in client performance.

3.3.4 Recursive Moving Average (MA)

The fourth deterministic method applies a three-month recursive simple moving average, where each new forecast is iteratively based on the most recent observed or projected values.
Formally, for a window size of $k = 3$, the forecast for client i at month t +1 is given by:

$$\widehat{M}_{i,t+1} = \frac{1}{k}\sum_{j=0}^{k-1} M_{i,t-j} \tag{9}$$

where $M_{i,t}$ represents either observed or previously forecasted contribution margins.

This recursive formulation smooths short-term variability and gradually stabilizes the projection path, preventing isolated shocks from propagating through the forecast horizon. The moving-average approach thus provides a conservative, stability-oriented benchmark consistent with the long-term dynamics of private-banking relationships. The intuitive three-month window $k = 3$ was chosen to capture the most recent quarterly dynamics of client performance - balancing responsiveness to new information with short-term smoothing that reflects managerial decision cycles in wealth management.

3.3.5 Summary of Projections

Applying the four projection methods to each client's monthly contribution margin generates 12-month-ahead cash-flow series for all individuals. Table 2 presents descriptive statistics, enabling distributional comparison across methods.

Table 2: Descriptive statistics of monthly margin projections

Statistic	AMGR	CAGR	Sen's Slope	MA
Mean	17,982.91	17,621.21	17,604.13	15,899.06
Median	10,534.67	10,338.32	10,317.17	10,182.81
Std. dev.	21,321.28	20,453.48	21,611.71	16,899.89
Minimum	14.26	35.76	31.86	100.00
1st quartile	4,400.69	4,357.56	4,381.70	4,589.70
3rd quartile	25,966.06	25,737.81	25,076.82	22,829.81
Maximum	360,707.90	308,171.40	331,026.12	257,255.44

Note: Values are expressed in current Brazilian reais (R$) over a 12-month projection horizon.

The mean-growth method yields the highest averages and maxima, reflecting sensitivity to large positive variations. In contrast, the moving-average approach produces more conservative forecasts, characterized by lower means, smaller dispersion, and a narrower interquartile range. The CAGR and Sen's slope projections exhibit similar central tendencies, effectively capturing gradual growth or decline across clients. Together, these deterministic methods provide a balanced view of expected future margins - ranging from reactive to trend-based and smoothed perspectives - and serve as inputs to the CLV computation in the following section.
The projected series obtained from these four methods form the foundation for the valuation stage. In the next section, we integrate these forecasts with client-specific discount rates - adjusted for idiosyncratic and systematic risk - to compute individual Customer Lifetime Values (CLVs) and aggregate Customer Equity (CE). This integration links the behavioral and financial dimensions of the model, allowing the contribution of each client to be expressed in present-value terms while accounting for risk and retention.

3.4 Discount Rate Construction

Standard CLV models typically apply a constant discount rate, implicitly assuming homogeneity in intertemporal risk across customers. We depart from this assumption by allowing the discount rate r_i to vary according to each client's exposure to idiosyncratic and systematic risk. Formally, the Customer Lifetime Value (CLV) for customer i is defined as:

$$\boldsymbol{CLV_i} = \sum_{\{t=1\}}^{T} \frac{\boldsymbol{M_{i,t}}}{(\boldsymbol{1}+\boldsymbol{r_i})^{\boldsymbol{t}}} \tag{10}$$

where $\boldsymbol{M_{i,t}}$ denotes the forecasted contribution margin and r_i the individual-specific discount rate.

3.4.1 Idiosyncratic Risk

Customer-specific volatility σ_i is measured from the preprocessed monthly margin series and serves as a proxy for idiosyncratic risk. To reflect the relative deviation of each client's volatility from the portfolio average, the rate adjustment is defined as:

$$r_i = r_f + (\sigma_i - \bar{\sigma}) \tag{11}$$

where r_f is the monthly risk-free rate and $\bar{\sigma}$ represents the mean cross-sectional volatility. This formulation penalizes higher-than-average volatility with higher discount rates while rewarding clients whose margins display greater stability.

3.4.2 Systematic Risk

Systematic exposure is captured through a CAPM-inspired specification:

$$r_i = r_f + \beta_i \cdot (\bar{r}_m - r_f) \tag{12}$$

where β_i is estimated by regressing individual returns on the internal market benchmark $\bar{r}_m$, computed as the average return of all active clients. Clients whose margins co-move strongly with the aggregate portfolio (higher β_i) are assigned higher discount rates, reflecting greater systematic sensitivity.

3.4.3 Score-Based Transformation

Because the empirical ranges of σ_i and β_i differ, we implement a normalized score transformation that maps each risk measure to a comparable 0–100 scale. Let $Score_{k,i} \in [0,100]$ denote the standardized idiosyncratic, systematic, or composite risk score for customer i The transformation:

$$r_i = r_f \left(0.5 + \frac{Score_{k,i}}{100}\right) \tag{13}$$

constrains $ri \in [0.5rf, 1.5rf]$ while preserving the relative ranking of clients by risk exposure. This normalized mapping produces interpretable and bounded discount rates, facilitating comparison across models and graphical diagnostics.

3.4.4 Integrated Risk

In practice, idiosyncratic and systematic risk components are computed separately and then combined to obtain a total risk-adjusted rate:

$$r_i^{Total} = r_f \left(0.5 + \frac{Score_{idio,i} + Score_{syst,i}}{200}\right) \tag{14}$$

This composite specification assigns equal weight to both risk dimensions and ensures that all rates remain consistent with the same bounded scale. Each resulting rate is then compared against the baseline risk-free rate rf, producing variation diagnostics and classification into below- and above-benchmark groups. Finally, these risk-adjusted rates are applied to all projection models (AMGR, CAGR, Sen's Slope, and Moving Average), both with and without the constant survival factor $(s = 0.60)$. This unified structure enables the evaluation of Customer Lifetime Value (CLV) and Customer Equity (CE) under distinct behavioral and risk-adjusted conditions, thereby linking client heterogeneity to portfolio-level value creation.

<u>Ilustration</u>

Table 3 illustrates the score-based specification for a client with constant monthly margins of 10,000 currency units over a 12-month horizon, assuming rf = 0.8%. An average-risk profile (Score $=$ 50) yields r_i = 0.8% and a CLV of 116,670. A defensive profile (Score $=$ 10) lowers r_i to 0.48% and raises CLV to 117,960, whereas an aggressive profile (Score $=$ 90) increases r_i to 1.12% and reduces CLV to 115,470.

Table 3: Effect of risk scores on discount rate and CLV

Profile	Score	r_i (%)	CLV (R$)
Average-risk	50	0.800	116,670.00
Defensive	10	0.480	117,960.00
Aggressive	90	1.120	115,470.00

Note: CLV values based on 12-month projection with constant monthly margins of R$10,000 and monthly risk-free rate, r_f = 0.8%.

3.4.5 Portfolio Aggregation

While CLV is defined at the individual level, private banking decisions ultimately depend on a portfolio view of the customer base. Aggregating across clients yields the portfolio-level Customer Equity (CE),

$$CE = \sum_{i=1}^{N} CLV_i \tag{15}$$

which represents the total present value of all expected customer cash flows-analogous to the valuation of a diversified portfolio of financial assets.

This aggregation is essential because it links the heterogeneity of individual clients to the collective performance of the portfolio. In practice, customers differ in both profitability and risk exposure: some exhibit high volatility or strong co-movement with market conditions, while others contribute more stable but moderate cash flows. When combined, these profiles interact in ways that can either amplify or smooth overall portfolio risk, reflecting a diversification mechanism similar to that observed in finance.

By applying individualized discount rates that capture idiosyncratic and systematic risk, the resulting CE internalizes the composition and structure of the customer base. Portfolios dominated by few, high-risk clients will yield lower and more volatile CE estimates, whereas more diversified portfolios - composed of many low-volatility and weakly correlated clients - tend to generate more stable aggregate value.

When survival-adjusted flows are used, by replacing $M_{i,t}$ with $M_{i,t} \cdot s_{i,t}$, the measure also reflects relationship persistence, providing a consistent foundation for the empirical analyses presented in the next section.

4. Results

Building on the methodological framework, we now evaluate how individualized discount rates affect customer valuation both at the individual and portfolio levels. This analysis connects the micro-level heterogeneity captured in client-specific CLVs with the macro-level implications for aggregate Customer Equity (CE), illustrating how risk-adjusted valuation modifies the overall structure of portfolio value.

We apply the individualized discount rates described in Section 3 to the projected monthly contribution margins and compute both Customer Lifetime Value (CLV) at the client level and aggregate Customer Equity (CE). Clients are evaluated under three risk specifications: (i) idiosyncratic, based on individual volatility; (ii) systematic, based on each client's beta relative to the portfolio benchmark; and (iii) composite, which combines both risk components into a single discount rate.

To isolate the effect of retention, we also apply a constant monthly survival factor ($s = 0.60$) directly to projected margins. As expected, this adjustment scales future cash flows downward in approximately the same proportion (e.g., AMGR with the standard rate declines from R$201,101 to R$120,661), without altering the relative ordering of models or discount-rate specifications.

Figure 2 summarizes the mean CLV per client across projection methods and discount-rate structures. Valuation levels differ across forecasting approaches - AMGR produces the highest averages, while the moving-average method yields the lowest - yet the ranking of discount-rate specifications remains stable within each projection method. This indicates that introducing client-level risk does not generate noisy or erratic valuations; instead, it shifts levels in a systematic and interpretable way.

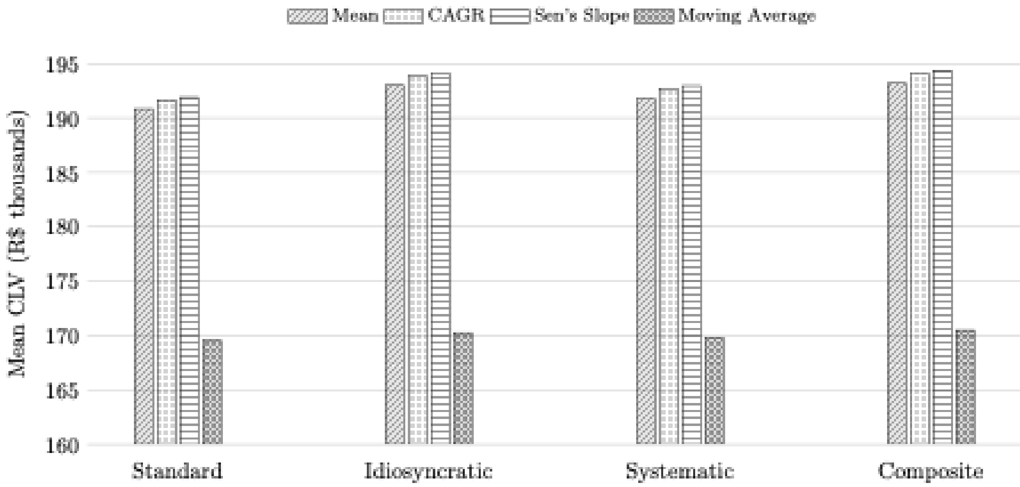

Figure 2: Mean CLV per client (R$ thousands) by projection method, across discount-rate specifications

Table 4 reports mean CLV and total CE for all combinations of projection method, discount-rate specification, and survival adjustment. Across projection techniques, AMGR yields the largest valuations, followed by CAGR and Sen's slope, whereas the moving-average method generates more conservative estimates. These differences are expected, given that AMGR and CAGR are more sensitive to recent positive margins, while the moving average smooths short-run volatility.

Across risk specifications, the composite rate produces the largest adjustment relative to the standard benchmark, followed by the idiosyncratic rate, while the purely systematic effect is slightly smaller. Numerically, these differences appear modest (typically 0.4%--1.1% of CLV), but they are economically meaningful in private banking portfolios: clients with below-benchmark volatility and beta preserve more value when discounted at individualized rates, whereas high-volatility or highly market-sensitive clients see their CLV reduced. In other words, the risk-adjusted framework reallocates value toward more stable relationships, which is consistent with service-intensive settings where pricing, staffing, and retention decisions are made at the client level.

Robustness checks (not tabulated) confirm that higher discount rates mechanically reduce both CLV and CE, but they do not reverse the relative ranking of either forecasting methods or risk specifications. This suggests that the framework is capturing underlying behavioral and financial dynamics in the data rather than artifacts of model choice. The next section discusses how these results can be translated into managerial policies for private banking.

Table 4: CLV and Customer Equity Results

Projection	Rate Type	Survival	Mean CLV (R$)	Customer Equity (R$)
AMGR	Standard	No	201,101.37	190,845,198.53
AMGR	Standard	Yes	120,660.82	114,507,119.12
AMGR	Composite	No	202,270.93	191,955,111.97
AMGR	Composite	Yes	121,362.56	115,173,067.18
AMGR	Systematic	No	202,199.51	191,887,338.02
AMGR	Systematic	Yes	121,319.71	115,132,402.81
AMGR	Idiosyncratic	No	202,406.46	192,083,733.74
AMGR	Idiosyncratic	Yes	121,443.88	115,250,240.24
CAGR	Standard	No	197,123.53	187,070,233.82
CAGR	Standard	Yes	118,274.12	112,242,140.29
CAGR	Composite	No	198,279.01	188,166,781.01
CAGR	Composite	Yes	118,967.41	112,900,068.60
CAGR	Systematic	No	198,126.76	188,022,291.09
CAGR	Systematic	Yes	118,876.05	112,813,374.65
CAGR	Idiosyncratic	No	198,492.41	188,369,298.03
CAGR	Idiosyncratic	Yes	119,095.45	113,021,578.82
Sen's Slope	Standard	No	196,878.43	186,837,629.85
Sen's Slope	Standard	Yes	118,127.06	112,102,577.91
Sen's Slope	Composite	No	197,995.48	187,897,710.90
Sen's Slope	Composite	Yes	118,797.29	112,738,626.54
Sen's Slope	Systematic	No	197,701.51	187,618,733.17
Sen's Slope	Systematic	Yes	118,620.91	112,571,239.90
Sen's Slope	Idiosyncratic	No	198,346.57	188,230,895.65
Sen's Slope	Idiosyncratic	Yes	119,007.94	112,938,537.39
MA	Standard	No	178,123.92	169,039,601.25
MA	Standard	Yes	106,874.35	101,423,760.75
MA	Composite	No	179,156.73	170,019,734.57
MA	Composite	Yes	107,494.04	102,011,840.74
MA	Systematic	No	178,649.98	169,538,831.77
MA	Systematic	Yes	107,189.99	101,723,299.06
MA	Idiosyncratic	No	179,711.01	170,545,749.43
MA	Idiosyncratic	Yes	107,826.61	102,327,449.66

Note: CLV is the average present value per client (R$), and CE is the aggregate across the sample. Values are expressed over a 12-month horizon. "Survival" indicates whether the survival factor was applied.

5. Conclusion

The empirical evidence supports the main premise of this study, showing that incorporating both systematic and idiosyncratic risk into customer valuation fundamentally changes how client value is measured and interpreted in private banking. When discount rates are tailored to each client's volatility and beta, estimates of Customer Lifetime Value (CLV) and aggregate Customer Equity (CE) become more differentiated, reflecting the real diversity of financial behavior within the portfolio. Even in a stable client base, differences in risk exposure generate meaningful variations in valuation, revealing that apparent stability can mask significant heterogeneity in underlying risk profiles. The downward adjustment observed for most clients is consistent with the defensive, low-volatility pattern identified in Section 4, suggesting that conservative relationships, while stable, contribute less to portfolio growth once risk is explicitly priced.

Quantitatively, the effects are moderate in scale but economically relevant. Without the survival adjustment, the composite rate produces the largest differential—approximately R$2.1 thousand per client (about 1.0–1.1%) and R$1.17 million in aggregate CE—followed by the idiosyncratic component (roughly 0.9–1.0%). The systematic factor exerts a smaller yet consistent influence (around 0.4%). When the survival factor is applied, valuations decline proportionally, but the relative ordering of projection methods and discount-rate specifications remains stable. Over extended horizons, these differences would accumulate, implying greater divergence between standard and risk-adjusted valuations and influencing long-term strategic decisions.

Beyond the numerical results, the findings validate the conceptual premise that integrating multiple dimensions of financial risk provides a more stable and realistic representation of client value. The composite discount rate balances the effects of volatility and market sensitivity, yielding a defensible and interpretable measure of risk-adjusted value. This logic mirrors portfolio management principles, where diversification across heterogeneous assets - or clients - reduces aggregate volatility without sacrificing expected return. By treating customers as financial assets with distinct risk-return profiles, Customer Equity becomes a natural extension of asset valuation principles to the domain of client management.

From a managerial standpoint, the framework enhances customer valuation by introducing financial discipline into the assessment of long-term relationships. It allows decision-makers to align pricing, advisory effort, and service intensity with each client's contribution to portfolio stability and profitability. This facilitates more efficient resource allocation across client segments and enables the design of service strategies that account for both value potential and risk exposure. In capital-intensive, relationship-based businesses such as private banking, this alignment between financial rigor and service management is essential for sustaining performance and accountability.

The parameters used in this study - time horizon, risk-free rate, and risk metrics - were calibrated for proof of concept and can be readily adapted to other financial service settings. Future research may refine survival estimation, incorporate behavioral dimensions, or test alternative macroeconomic conditions. Extensions could also examine dynamic discounting mechanisms linked to client or market volatility to enhance predictive and managerial precision.

In conclusion, this research provides an empirically validated and financially consistent framework for embedding risk sensitivity in customer valuation. By integrating risk-adjusted discounting with service-based relationship management, it bridges the analytical rigor of finance with the relational complexity of service operations. The approach offers a practical tool for pricing, client prioritization, and portfolio planning - helping financial institutions to manage their customer base as a portfolio of long-term, risk-adjusted assets.

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