Lisbon School of Economics & Management
Universidade de Lisboa

# MASTER'S IN
FINANCE

# MASTER'S FINAL WORK
PROJECT

# EQUITY RESEARCH CTT CORREIOS DE PORTUGAL: ASSESSING AI-BASED FORECASTING FOR BANK VALUATION THE BANCO CTT CASE

ALEXANDER MAXIMILIAN LORENZL

JUNE 2025

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# Abstract

The valuation of banks is complex due to several factors: special regulatory capital requirements, balance sheet dynamics where deposits serve as both liabilities and funding sources and interest rate risk exposures that render traditional cash flow metrics unreliable. Given the complexity, this study aims to answer whether machine learning can generate credible stand-alone bank valuations using public financial and macroeconomic data, while identifying influential drivers. A neural network was trained on 103 features from 415 European banks (1999–2024) to forecast P/B ratios, employing chronological splits to prevent look-ahead bias.

The results show that the artificial neural network was unable to generate reliable valuations: test-set $R^2$ (–2.87), MSE (4.09) and MAE (0.53) exceeded 50% of the mean P/B ratio (≈1), performing worse than a naive mean predictor. However, integrated gradients identified economically relevant drivers: ROE increased P/B, while loan-loss provisions and surplus deposits decreased it, aligning with traditional valuation theory.

Based on these findings, it can be concluded that while machine learning is unable to replace analyst-led valuation for novel cases, it is effective in quantifying universal drivers. The model's inability to fully price instrument-specific aspects leads to the conclusion that human input is still required. This information is critical for analysts, financiers and regulators, as it highlights that the assessment of intrinsic value cannot yet be fully delegated to algorithms. In summary, although AI has the potential to accelerate valuation workflows, expert judgement is still necessary for accuracy in cases where firm-specific nuances matter.

JEL classification: C30; C40; C45; G10; G17; G32

Keywords: Equity Research; Valuation; Bank Valuation; Machine Learning, Neural Networks, Feature Importance

# Resumo

A avaliação de bancos é complexa face a diversos fatores: exigências especiais de capital regulamentar, dinâmicas do balanço em que os depósitos funcionam simultaneamente como passivos e fontes de financiamento, e exposições ao risco de taxa de juro que tornam as métricas tradicionais de fluxo de caixa pouco fiáveis. Perante esta complexidade, este estudo visa responder se a Aprendizagem Automática pode produzir avaliações bancárias autónomas credíveis, utilizando dados financeiros e macroeconómicos públicos, e identificar os impulsionadores relevantes. Uma Rede Neural foi treinada com 103 variáveis de 415 bancos Europeus (1999–2024) para prever P/B, utilizando divisões cronológicas para evitar enviesamento de antecipação.

Os resultados demonstram que a Rede Neural artificial não conseguiu produzir avaliações fiáveis: o $R^2$ do teste (–2,87), o MSE (4,09) e o MAE (0,53) excederam 50% do rácio P/B médio (≈1), com desempenho inferior ao de um preditor ingénuo da média. Contudo, os gradientes integrados identificaram impulsionadores economicamente relevantes: o ROE aumentou o P/B, enquanto as provisões para créditos incobráveis e os depósitos excedentários o reduziram, alinhando-se com a teoria de avaliação tradicional.

Com base nestas conclusões, infere-se que, embora a Aprendizagem Automática não substitua a avaliação conduzida por analistas em casos novos, mostra-se eficaz na quantificação de impulsionadores universais. A incapacidade do modelo em refletir plenamente nos preços os aspetos específicos dos instrumentos leva a concluir que o contributo humano permanece necessário. Esta informação é crucial para analistas, financiadores e reguladores, pois evidencia que a avaliação do valor intrínseco ainda não pode ser totalmente delegada a algoritmos. Em síntese, embora a IA tenha potencial para acelerar fluxos de trabalho de avaliação, o juízo especializado mantém-se indispensável para a precisão em casos onde intervêm nuances específicas da empresa.

Classificação JEL: C30; C40; C45; G10; G17; G32

Palavras-Chave: Equity Research; Avaliação; Avaliação de Bancos; Aprendizagem Automática, Redes Neuronais, Importância das Caraterísticas

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# Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| BCP | Banco Comercial Português |
| BCTT | Banco CTT |
| Bps | Basis Points |
| BU | Business Unit |
| CAGR | Compound Annual Growth Rate |
| CAPEX | Capital Expenditures |
| CET1 | Common-Equity Tier 1 |
| CGD | Caixa Geral de Depositos |
| CPI | Consumer Price Index |
| DCF | Discounted Cash Flow |
| ECB | European Central Bank |
| EIU | Economist Intelligence Unit |
| ESG | Environmental, Social and Governance |
| EU | European Union |
| FCFE | Free Cash Flow to Equity |
| FY | Fiscal Year |
| GDP | Gross Domestic Product |
| IBL | Interest Bearing Liabilities |
| IEA | Interest Earning Assets |
| LTD | Loan to Deposits |
| MAE | Mean Absolute Error |
| ML | Machine Learning |
| MRP | Market Risk Premium |
| MSE | Mean Squared Error |
| NARX | Nonlinear Autoregressive Model with Exogenous Input |
| NI | Net Income |
| NII | Net Interest Income |
| NIM | Net Interest Margin |
| NPL | Non-Performing Loans |
| OPEX | Operating Expenditures |
| P/B | Price-to-Book |
| P/E | Price-to-Earnings |
| P/TBV | Price-to-Tangible-Book |
| P/TBV | Price-to-Tangible-Book Value |
| ROA | Return on Assets |
| ROE | Return on Equity |
| RWA | Risk Weighted Assets |
| Sh | Share |
| SoP | Sum of the Parts |
| TLTRO | Targeted Longer-Term Refinancing Operations |
| USP | Unique Selling Proposition |

# 1. Introduction

In his book, Damodaran (2009) examines the valuation of financial service firms as a long-standing challenge in corporate finance. Bank balance sheets combine operating liabilities with deposits and regulatory capital requirements constrain leverage, while interest-rate risk is present on both sides of the balance sheet. Classic valuation approaches therefore are not applicable as financial institutions have different valuation mechanisms.

Since discounted-cash-flow (DCF) is impractical in these circumstances, analysts have gravitated towards relative valuation, particularly price-to-earnings (P/E) and price-to-book (P/B) multiples. A comprehensive study by Massari et al. (2018) of U.S. and European banks in a panel from 1990 to 2017 demonstrates that those two multiples explain a larger share of market prices than alternative ratios such as price-to-assets or dividend yield. Nevertheless, the most effective multiple still produces economically large errors, especially when profitability, risk and regulatory conditions differ from peer values. This is particularly relevant whenever banks are part of a larger economic group with diversified non-financial industries.

A relevant example of this is the Portuguese CTT Group where part of their segments is Banco CTT. Valuing banks that are part of non-financial groups by nature, as is the case at Banco CTT, yields additional layers of complexity that- traditional valuation approaches do not fully address. The CTT Group is typically valued using a sum-of-the-parts analysis, based upon which Banco CTT is assigned an equity figure through traditional multiple- and income-based methods. This study revisits the banking segment of the CTT group with a machine-learning (ML) approach to determine whether a data-driven model can estimate the value of this unlisted bank and, in doing so, alter its implied contribution to the group.

Empirical evidence suggests that for equity valuation, ML-based models that learn optimal peer-weights can outperform conventional industry averages to determine sources of profitability, identify significant mispricing signals and determine their respective fair value (Almaskati, 2022; Geertsema & Lu, 2023; Hanauer et al., 2022). Despite this progress it remains unclear if ML models can deliver an initial valuation for a financial institution when no prior market price or analyst estimate exists. To be precise, if an algorithm is trained exclusively on cross-sectional financial-statement and macroeconomic data, can it generate a stand-alone estimate of intrinsic value for a previously unvalued bank? If so, how does that value compare to the one determined by a human analyst using a traditional approach? The resolution of this issue is significant, as an initial valuation can shape strategic and regulatory dialogue and influence capital allocation. This issue is particularly relevant in the context of Banco CTT, where the bank's finances are closely linked to CTT's logistics platform. This complicates cost structures and makes it difficult to apply the usual methods used for standalone banks. In the absence of a trading record, a data-driven valuation emerges as a neutral way to determine the bank's intrinsic value. Moreover, this research offers investors and supervisors perspective on which variables the algorithm determines most significant and as a result potentially confirming, refining or challenging the importance of features in traditional bank-valuation practice.

This work is therefore structured with the aim of answering the following research question:

**Can an ML model trained on publicly available financial-statement and macroeconomic data deliver a credible standalone valuation of a bank and identify the variables it considers most influential in that valuation?**

To answer this question effectively, this work is structured in the following manner. Chapter 2 reviews the current literature on bank valuation and ML applications in finance. The gathered data, variable and feature creation process and processing steps are covered in Chapter 3. Chapter 4 details the modeling technique, including network architecture, training strategy and performance metrics. The accuracy and results of the ML-derived value for Banco CTT are compared to the one obtained from the conventional valuation in Chapter 5. Chapter 6 will form a conclusion, address limitations and offer recommendations for further research.

# 2. Literature Review

Accurately determining the value of companies is one of the central challenges in finance. Initially, expert analysts' models and fundamental analysis have guided valuation. According to Damodaran (2012, p. 25) the approaches can be classified into DCF, relative valuation and contingent claim valuation. Although these are based on financial theory, they also heavily rely on analyst judgment and a number of assumptions (Kruschwitz & Löffler, 2005, pp. 9–11). Key inputs (e.g. future cash flows, growth rates, discount rates or comparables) must be subjectively determined by analysts, which can introduce biases and variation in valuations. Bogatyrev (2019) and Green et al. (2016) both argue that DCF and other valuation methods are unable to deliver unbiased business valuations due to its significant reliance on analyst assumptions since any outcome for a valuation can be supported by adjusting relevant input variables. Herman et al. (2024) voice a more critical opinion and characterize traditional methods such as DCF as “outdated” and “failing to capture all value factors”, especially in dynamic markets. Despite the refinement of these methods over decades, the studies clearly show that there is still no valuation method available which is without drawbacks.

Purely quantitative models generate interest in more objective approaches, as those are less susceptible to the potential downsides of bias. Human experts, however, provide qualitative judgment and context, which quantitative models do not capture. Shaffer & Wang (2024) point out that "judgment and integration of information scattered throughout financial disclosures, contextualized with general industry knowledge," is needed to assess a company's actual earning power. Demonstrated by the study from Cao et al. (2021), experienced analysts excel at combining such unstructured data, e.g. appraising management quality or industry knowledge, that is challenging to represent into a conventional quantitative model. This kind of qualitative integration is both a strength of human analysis and a source of inconsistency since two analysts might weigh soft factors differently. This has motivated academics as well as practitioners to search for more consistent, data-driven ways which could complement or enhance the conventional approach to valuation (Gu et al., 2020; Van Binsbergen et al., 2023).

Empirically, AI valuation models are often able to outperform or at minimum equal human-based models. Wilimowska & Krzysztoszek (2013) presented an early feasibility on the use of an Artificial Neural Network (ANN), combining asset- and income-based inputs for the valuation of companies. Later studies consistently support this possibility. Dhochak et al. (2024) discovered ANNs significantly outperformed linear regression in startup valuation, therefore suggesting their potential for being used as complements or even replacements for traditional valuation techniques. Likewise, Herman et al. (2024) observed neural networks surpassing conventional techniques as the latter one not being able to capture all nuances and hybrid models, which combine different approaches, being especially accurate. Guner & Unal (2023) demonstrate the effectiveness of a Nonlinear Autoregressive Model with Exogenous Input (NARX) neural network in predicting year-ahead values by learning solely from the historical ratios. These studies serve as evidence for the effectiveness of Artificial Intelligence (AI) in capturing complex, nonlinear connections that are not being picked up on in traditional equity analysis (Ahangar et al., 2010; Fischer & Krauss, 2018; Gu et al., 2020; Kamalov et al., 2020; Tuttle et al., 2021).

However, the effectiveness of AI models depends on their design, effective customization for the specific task and enough training data with relevant features. As outlined by Vayas-Ortega et al. (2020), the combination of endogenous value creating variables, analogue to the ones being used for a traditional DCF, and context-specific information, e.g. industry or country specific, yield the highest accuracy in AI models. This demonstrates that to be accurate, valuation models have to take into account both industry and firm-specific features (Hawawini et al., 2003). Consequently, valuing businesses with unique features reveals several limitations. Specifically, algorithms trained on general patterns are not capable of performing effectively on unusual business models, one-time events, or general aspects that are not showcased in the training data. Particularly in the case of specialized or smaller companies, where local knowledge has the potential to be a significant driver of value, this restriction is evident. Therefore, while AI has the capability to perform well in trained environments with thorough data, its capabilities reduce when confronted with distinct entities or unforeseen situations that have not been present in the training data.

Overall, the literature showcases that the challenge in determining the value of companies persists and neural networks serve as a viable or even superior approach to assessing company values. ML models have demonstrated the ability to incorporate diverse inputs and uncover complex relationships, leading to accurate valuations in numerous studies. However, traditional valuation methods emphasize that experience, contextual understanding and qualitative judgment are essential for quantifying a firm's value, aspects that algorithms have difficulty in capturing, as those effects are difficult to quantify in numbers. The studies presented indicate a growing recognition for the combination of the strengths of AI and human analysis and on finding ways to best complement them.

Using the presented studies as basis, this work aims to investigate the accuracy of an AI model for forecasting the market value of a bank based not on prior market valuations but balance sheet data and macroeconomic indicators. Subsequently, the model will be compared to a traditional analyst-driven valuation. The goal is to critically assess to what extent the AI model can improve upon the insights of a traditional analysis in this context. By doing so, it can be identified which factors determine the value based on the AI-model and if the optimal solution might be a hybrid approach that builds upon both a data-driven algorithm in combination with an analyst's judgment.

# 3. Data

This work uses a dataset of European banks to develop a forecast model for bank valuation multiples. The data covers annual observations from 1999 to 2024 and was gathered from 415 publicly traded banks in Europe. The data was compiled from Bloomberg and consists of bank-specific financial metrics. Each bank-year observation contains numerous variables capturing the bank's balance sheet, income statement and market data. This dataset provides the foundation for predicting the three variations of the valuation ratio P/B multiple one year ahead. An overview of collected features for each bank is shown in Appendix A.1.

## 3.1 Dependent Variables

The dependent variables are the low P/B, average P/B and high P/B for each bank on an annual basis. These correspond to the *lowest*, *average* and *highest* ratios of market P/B per share that the bank's stock reached within one given year.

$$Price\ to\ Book\ Ratio = \frac{Market\ Capitalization}{Book\ Value\ of\ Share\ Capital}$$

The P/B-ratio is a pricing metric, often interpreted as a measure of a bank's intrinsic value based on peers and investor expectations. A P/B > 1 indicates the market values the bank's equity above its accounting book value (implying strong future prospects), whereas a P/B < 1 signals concerns about the bank's profitability or assets (Bogdanova et al., 2018). The average P/B ratio is defined as the time-weighted average of the daily P/B values over the time period of one year. The high P/B and low P/B represent the extremes of the daily ratios during the year, effectively the maximum and minimum P/B observed. The desired objective for forecasting the high and low P/B, is to capture the expected range of valuation multiples for the coming year, while the average P/B forecasts can serve as indicator for the typical valuation level (Bogdanova et al., 2018).

## 3.2 Independent Variables

With the goal of explaining and accurately predicting P/B ratios, 103 bank financial indicators are used as independent variables (features). These features consist of metrics for growth, operational efficiency, liquidity and funding, capital ratios, asset quality and profitability.

Profitability measures that are considered as drivers for market valuations include Return on Equity (ROE) and Return on Assets (ROA). A higher ROE indicates that the bank is capable of generating higher profits from its equity, which drives a higher P/B. Since credit issues and other asset indicators have shown to affect valuations, asset quality indicators such as the ratio of non-performing assets are included (DV, 2024; Jordan et al., 2011). Capital ratios, such as tangible common equity or Tier-1 capital, serve as indicators for the bank's financial resilience, which has the potential to impact investor confidence and the P/B. For instance, ROE and ROA are conventional profitability metrics that influence market valuations; a higher ROE generally supports a higher P/B, all else being equal, as it signals the bank can generate more profit from its equity (Damodaran, 2025; Dayag & Trinidad, 2019; Martínez et al., 2024). Asset quality indicators, such as the ratio of non-performing assets, are included since studies have shown that credit problems and other asset indicators impact valuations (DV, 2024; Jordan et al., 2011). Capital ratios (Tier-1 capital, tangible common equity) measure a bank's financial resilience, which have demonstrated to affect investor confidence and thus P/B. Efficiency measures, e.g. the cost-to-income ratio and non-interest expense, are included since lower operating costs boost net earnings and result in a higher valuation. (Blokhin, 2023; Bogdanova et al., 2018; DV, 2024)

In addition to bank-specific data, the dataset incorporates 43 macroeconomic indicators and industry-wide variables that influence bank valuations as Ruxho & Beha (2024) have already found a significant impact of economic indicators on the profitability of banks. These indicators were collected at a European level (and thus apply to all banks for a given year). Notable examples include GDP growth rates, interest rate environment indicators and credit demand surveys. By including different economic factors, the goal is to capture the influence of broader economic conditions (systematic factors) on bank valuations.

In total 146 variables were extracted for each year from the financial statements and market data, of which a detailed overview is provided for the bank features in Table 1 and for the macroeconomic features in Table 2. Most of the features are expressed as ratios or growth rates although some are in absolute terms. All features were normalized prior to the training of the model, as detailed in Chapter 4.2. The rationale for including a broad set of features is to provide the model with multiple determinants of bank value identified in the previous literature for the neural network to most effectively learn the relationships between these factors and the resulting valuation multiples.

## 3.3. Data Processing and Control

The data from Bloomberg required processing and structuring prior to the implementation of the ML steps. Each bank's data was exported in the form of time series annual values for each variable. In the event that a bank had missing data for a variable in a given year, that year was not able to contribute to the training for a target that relies on that variable. In order to avoid the potential for bias, records were dropped for the terminal year of each bank. This decision was made due to the forecasting configuration requiring for each input record to be paired with a "next year" value for the target P/B ratio.

The final dataset used for training the model contained 5,088 bank-year observations available for subsequent steps. Basic descriptive statistics were computed to ensure the data's plausibility and are shown in Table 1 and Table 2. To reduce the influence of extreme values and with the goal of improving the model's accuracy several processing steps were performed which are detailed in subsequent chapters. Overall, the data collected provides an elaborate and detailed overview of European banks' financial situation and valuations over time. The dataset aims to capture the different drivers for P/B multiples in the banking industry, by combining firm-specific and macroeconomic information.

*Table 1: Overview sample metrics bank features*

| | N | Mean | Std. Dev. | p25 | Median | p75 |
|---|---|---|---|---|---|---|
| **Asset Quality** | | | | | | |
| Earning Assets | 4,793 | 97,204.64 | 270,318.25 | 1,005.55 | 39,506.04 | 8,095.44 |
| Loan Loss Reserve to Non-Perf Assets | 2,727 | 526.98 | 7,292.08 | 55.27 | 120.01 | 76.43 |
| Net Loans & Mortgages | 4,988 | 48,833.32 | 124,830.05 | 677.14 | 23,016.59 | 4,803.53 |
| Non-Perf Assets to Total Assets | 2,908 | 3.28 | 6.09 | 0.70 | 3.53 | 1.73 |
| Non-Perf Assets to Total Loans | 2,849 | 5.20 | 8.63 | 1.16 | 5.89 | 2.94 |
| Non-Performing Assets | 2,908 | 3,746.29 | 8,892.24 | 58.14 | 2,390.42 | 354.75 |
| Provision for Loan Loss to Total Loans | 4,162 | 0.86 | 2.05 | 0.11 | 1.03 | 0.42 |
| Provision for Loan Losses | 4,600 | 376.44 | 1,285.11 | 1.57 | 133.09 | 17.25 |
| Reserve for Loan Loss to Total Loans | 3,850 | 4.43 | 19.53 | 1.26 | 5.06 | 2.72 |
| Reserve for Loan Losses | 3,876 | 1,734.33 | 4,463.15 | 38.23 | 944.07 | 201.07 |
| Total Assets | 5,058 | 111,044.47 | 324,492.50 | 1,032.68 | 39,152.75 | 7,877.01 |
| Total Loans | 4,688 | 51,979.03 | 129,858.89 | 785.31 | 25,366.18 | 5,407.58 |
| Total Loans to Total Assets | 4,689 | 64.92 | 17.83 | 54.83 | 78.64 | 66.87 |
| **Capital Adequacy** | | | | | | |
| Basel Level Adopted Indicator | 2,486 | 2.63 | 0.78 | 3.00 | 3.00 | 3.00 |
| Book Value per Share | 5,036 | 25,593.50 | 408,907.28 | 4.59 | 83.81 | 18.76 |
| Risk-Weighted Assets | 2,835 | 64,767.20 | 139,240.70 | 1,763.39 | 50,919.48 | 8,481.44 |
| Tangible Book Value per Share | 4,484 | 19,765.50 | 343,031.06 | 3.93 | 74.83 | 16.59 |
| Tangible Common Equity | 4,503 | 5,562.54 | 14,298.99 | 135.05 | 3,474.39 | 806.56 |
| Tangible Common Equity Ratio | 4,504 | 9.26 | 7.71 | 5.54 | 11.49 | 8.30 |
| Tangible Common Equity to Risk-Weighted Assets | 2,739 | 5,855.40 | 220,704.51 | 11.65 | 19.50 | 15.34 |
| Tier 1 Capital Ratio | 3,101 | 14.73 | 13.57 | 11.06 | 17.53 | 14.30 |
| Total Capital Funds | 2,770 | 16,584.80 | 234,882.47 | 317.77 | 8,100.91 | 1,460.38 |
| Total Common Equity | 5,056 | 5,908.18 | 15,960.35 | 101.14 | 3,106.84 | 668.87 |
| Total Equity | 5,057 | 6,509.00 | 17,754.61 | 103.00 | 3,234.44 | 683.74 |
| Total Risk-Based Capital Ratio | 3,407 | 16.31 | 4.67 | 13.00 | 19.10 | 16.00 |
| **Growth** | | | | | | |
| Net Revenue Growth | 4,850 | 14.70 | 88.08 | -1.11 | 15.35 | 5.60 |
| Sustainable Growth Rate | 4,021 | 7.11 | 16.14 | 2.75 | 9.73 | 5.56 |

| | N | Mean | Std. Dev. | p25 | Median | p75 |
|---|---|---|---|---|---|---|
| **Liquidity & Funding** | | | | | | |
| Cash from Financing Activities | 4,193 | 1,753.77 | 12,338.98 | -7.05 | 794.81 | 57.39 |
| Cash from Investing Activities | 4,190 | -2,366.44 | 11,768.06 | -1,014.65 | -5.25 | -84.82 |
| Cash from Operations | 4,513 | 1,393.00 | 10,418.45 | -11.69 | 407.59 | 27.13 |
| Net Change in Cash | 4,304 | 850.35 | 8,703.35 | -27.82 | 236.31 | 10.27 |
| Total Deposits | 4,941 | 48,038.98 | 132,928.77 | 716.65 | 20,951.95 | 4,173.95 |
| Total Liabilities | 4,937 | 106,645.70 | 311,010.31 | 958.32 | 38,097.34 | 7,495.53 |
| Total Loans to Total Deposits | 4,642 | 126.11 | 79.63 | 83.31 | 139.41 | 110.48 |
| Operational Efficiency | | | | | | |
| Efficiency Ratio | 4,966 | 60.70 | 86.49 | 50.75 | 68.83 | 59.51 |
| Non-Interest Expense | 5,007 | 1,925.87 | 5,805.39 | 24.97 | 733.94 | 167.16 |
| Personnel Expenses | 4,786 | 864.53 | 2,358.31 | 13.51 | 359.28 | 87.13 |
| **Profitability** | | | | | | |
| 12-Month Net Interest Margin | 4,588 | 2.97 | 2.59 | 1.50 | 3.75 | 2.26 |
| Annualized Net Interest Margin | 4,587 | 2.99 | 2.78 | 1.51 | 3.75 | 2.27 |
| Annualized Return on Assets | 4,909 | 1.84 | 32.64 | 0.36 | 1.20 | 0.70 |
| Annualized Return on Common Equity | 4,892 | 8.26 | 24.04 | 4.11 | 13.29 | 8.18 |
| Basic Earnings per Share | 5,008 | -520.09 | 99,703.56 | 0.26 | 5.94 | 1.17 |
| Diluted EPS | 4,211 | -1,888.87 | 103,271.10 | 0.25 | 5.31 | 1.11 |
| Diluted EPS from Continuing Ops | 3,913 | -2,332.19 | 106,340.17 | 0.31 | 5.57 | 1.18 |
| Effective Tax Rate | 4,560 | 25.51 | 103.93 | 16.22 | 28.49 | 22.02 |
| Net Income Available to Common | 5,054 | 433.88 | 2,760.37 | 3.80 | 235.29 | 44.19 |
| Net Income to Common Margin | 5,042 | 18.75 | 84.01 | 11.22 | 28.87 | 19.95 |
| Net Interest Income | 5,001 | 1,524.48 | 4,004.82 | 24.66 | 806.98 | 158.97 |
| Net Interest Spread | 3,266 | -3.43 | 122.51 | 0.51 | 2.45 | 1.20 |
| Net Revenue | 5,014 | 2,909.09 | 8,432.36 | 40.40 | 1,319.46 | 287.05 |
| Net Revenue (Net of Commissions Paid) | 3,914 | 3,122.89 | 8,515.84 | 43.53 | 1,759.41 | 325.81 |
| Non-Interest Income | 5,014 | 1,388.50 | 5,226.17 | 11.92 | 510.52 | 104.99 |
| Operating Income or Losses | 5,060 | 647.78 | 3,021.48 | 6.78 | 319.05 | 66.23 |
| Operating Margin | 5,042 | 25.06 | 53.96 | 17.61 | 39.61 | 29.54 |
| Pre-Tax Pre-Provision Profit | 5,007 | 986.83 | 3,585.42 | 12.29 | 500.60 | 101.96 |
| Pre-Tax Pre-Provision Profit to Net Revenue | 4,991 | 34.97 | 52.88 | 29.09 | 46.79 | 38.28 |
| Pretax Margin | 5,039 | 26.31 | 96.88 | 17.12 | 39.19 | 28.73 |
| Profit Margin | 5,038 | -908.59 | 48,197.36 | 12.22 | 30.25 | 21.13 |
| Return on Assets | 4,909 | 0.80 | 1.72 | 0.36 | 1.19 | 0.71 |
| Return on Total Equity (Including Pref.) | 4,901 | 8.56 | 24.71 | 4.70 | 13.40 | 8.68 |

*Source: Raw data from Bloomberg, adapted*

*Table 2: Overview sample metrics macroeconomic features*

| | N | Mean | Std. Dev. | p25 | Median | p75 |
|---|---|---|---|---|---|---|
| Change in Expected Demand - Mortgages | 4,580 | -0.04 | 27.91 | -10.02 | 11.17 | 21.19 |
| Change in Expected Demand - Consumer Credit | 4,580 | 7.00 | 15.42 | -1.07 | 11.75 | 17.98 |
| Change in Expected Demand - Business | 4,580 | 10.69 | 16.01 | 1.03 | 10.85 | 24.91 |
| Eurozone Gross National Disposable Income | 2,813 | 2,154,161.36 | 239,861.00 | 1,973,421.10 | 2,244,672.80 | 2,343,139.60 |
| Total Lending Eurozone | 4,580 | 75.62 | 4.05 | 73.68 | 74.08 | 75.35 |
| Total Lending Non-Eurozone | 5,088 | 31.93 | 23.00 | 24.65 | 26.17 | 26.51 |
| Household Lending Eurozone | 5,088 | 99.96 | 0.01 | 99.95 | 99.96 | 99.96 |
| Household Lending Non-Eurozone | 5,088 | 0.04 | 0.01 | 0.04 | 0.04 | 0.05 |
| Household Lending - Mortages Eurozone | 5,088 | 99.95 | 0.01 | 99.95 | 99.95 | 99.95 |
| Household Lending - Mortages Non-Eurozone | 5,088 | 0.05 | 0.01 | 0.05 | 0.05 | 0.05 |
| Household Lending - Cons. Credit Eurozone | 5,088 | 99.96 | 0.01 | 99.96 | 99.96 | 99.96 |
| Household Lending - Cons. Credit Non-Eurozone | 5,088 | 0.04 | 0.01 | 0.04 | 0.04 | 0.04 |
| Household Lending - Other Lending Eurozone | 4,715 | 85.36 | 1.32 | 84.45 | 84.95 | 85.38 |
| Household Lending - Other Lending Non-Eurozone | 5,088 | 20.90 | 22.29 | 14.62 | 15.08 | 15.56 |
| Corporate Lending Eurozone | 5,088 | 99.98 | 0.00 | 99.98 | 99.98 | 99.98 |
| Corporate Lending Non-Eurozone | 5,088 | 0.02 | 0.00 | 0.02 | 0.02 | 0.02 |
| Eurozone Rates All Maturities | 4,969 | 3.10 | 1.30 | 1.82 | 3.11 | 3.81 |
| Consumer Confidence Indices % Eurozone | 5,088 | -11.38 | 5.55 | -13.70 | -11.60 | -7.30 |
| Consumer Confidence Indices % EU 28 | 5,088 | -10.79 | 5.52 | -12.80 | -10.70 | -6.40 |

| | N | Mean | Std. Dev. | p25 | Median | p75 |
|---|---|---|---|---|---|---|
| Household Consumption YoY % Eurozone | 5,088 | 0.99 | 2.54 | 0.30 | 1.40 | 1.80 |
| Household Consumption YoY % EU 28 | 5,088 | 1.18 | 2.51 | 0.20 | 1.60 | 2.10 |
| 3 Month Euribor | 5,088 | 1.27 | 1.70 | -0.32 | 0.70 | 2.87 |
| 12 Month Euribor | 5,088 | 1.52 | 1.70 | -0.12 | 1.25 | 3.05 |
| GDP constant price growth YoY % EU 28 | 5,088 | 1.47 | 2.08 | 0.90 | 1.70 | 2.50 |
| GDP constant price growth YoY % Eurozone | 5,088 | 1.30 | 2.11 | 0.70 | 1.50 | 2.30 |
| GDP breakdown Eurozone | 5,088 | 2,510,331.53 | 191,908.48 | 2,418,981.90 | 2,477,286.10 | 2,688,800.20 |
| GDP breakdown Household Expenditures | 5,088 | 1,365,399.75 | 76,935.32 | 1,332,367.50 | 1,358,317.90 | 1,445,955.70 |
| GDP breakdown Government Expenditures | 5,088 | 531,000.21 | 49,995.92 | 497,112.10 | 522,829.40 | 568,351.60 |
| GDP breakdown Fixed Capital Expenditures | 5,088 | 534,631.31 | 51,674.43 | 486,484.50 | 529,437.50 | 587,078.70 |
| GDP breakdown Export | 5,088 | 1,084,739.33 | 241,343.89 | 901,945.80 | 1,045,338.20 | 1,304,623.20 |
| GDP breakdown Import | 5,088 | 1,018,194.81 | 218,011.37 | 877,564.00 | 943,492.00 | 1,225,608.60 |
| EU 28 Tax Receipts % GDP | 4,074 | 26.33 | 0.59 | 25.70 | 26.60 | 26.80 |
| EU 28 Budget Balance % GDP | 4,074 | -2.58 | 1.73 | -3.30 | -2.50 | -1.00 |
| EU 28 Budget Balance % GDP Eurozone | 5,088 | -2.96 | 1.88 | -3.90 | -2.70 | -1.50 |
| Unemployment Rates % Eurozone | 5,088 | 9.02 | 1.60 | 7.90 | 8.70 | 10.20 |
| Unemployment Rates % EU 28 | 4,969 | 8.65 | 1.69 | 7.10 | 8.80 | 9.90 |
| CPI % EU 28 CPI (yoy %) | 5,088 | 2.48 | 2.27 | 1.30 | 2.10 | 3.00 |
| CPI % Eurozone | 5,088 | 2.15 | 2.04 | 1.10 | 1.90 | 2.50 |

*Source: Raw data from Bloomberg, adapted*

# 4. Methodology

## 4.1 Overview of Forecasting Approach

The forecasting goal is to predict next year's valuation multiples in terms of the low, average and high P/B ratios from information available as of the current year. The ML model is a neural network, capable of learning from patterns existing in a set of input features by describing the bank's financial condition in a given year to forecast the following year's P/B ratios.

$$X_{i,t} = (\text{Financial ratios of bank } i \text{ in year } t, \text{ Macroeconomic indicators in year } t)^{\top}$$

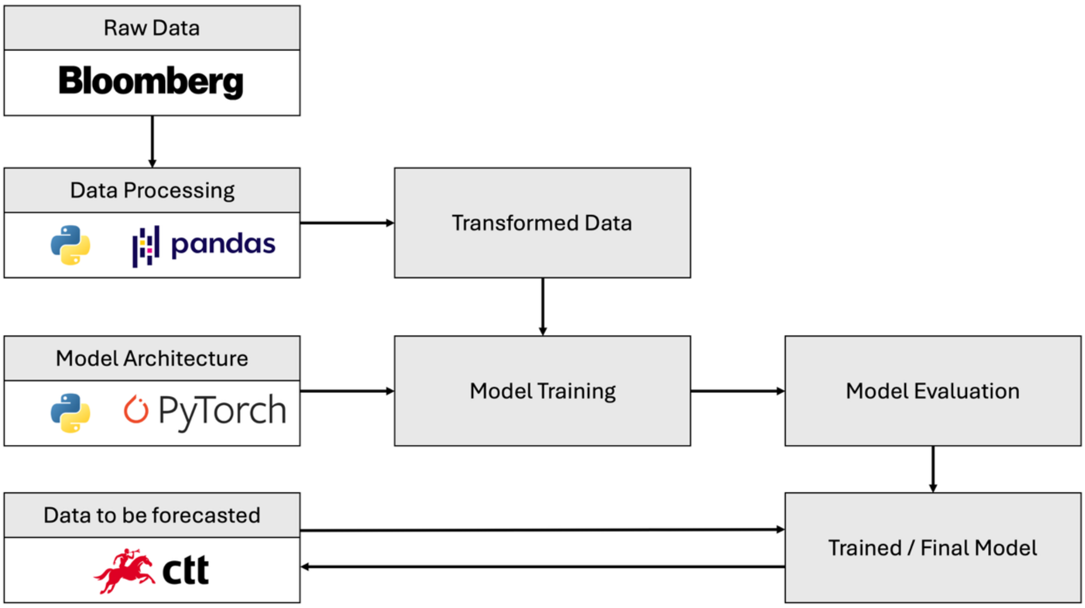
$$\mathbf{y_{i,t+1}} = \left(\text{Low P/B}_{i,t+1}, \text{ Avg P/B}_{i,t+1}, \text{ High P/B}_{i,t+1}\right)^{\top}$$

$$Forecast\ model\colon \mathbf{y_{i,t+1}} = f\left(\mathbf{X_{i,t}}\right) + \boldsymbol{\varepsilon}_{i,t+1}$$

Notably, look-ahead bias is avoided by ensuring that only information which is known by the end of year *t* is used to predict year *t+1*. The implementation of this process involved a structured shift in the data and model training. Specifically, for each record, all three price-to-book ratio targets were extracted from the subsequent year, while the independent features were obtained from the current year. Bank-years without a next year P/B were excluded, as noted in the Data section.

As illustrated in Figure 1, the methodology consists of a series of implemented steps and phases. Each step is described in detail in the respective chapter, outlining the actions performed as well as rationale explaining why respective actions have been implemented.

*Figure 1: Overview Methodology Steps*




*Source: Own Graphic, adapted from* (*Data Preprocessing for ML: Options and Recommendations*, 2024)

## 4.2 Data Processing and Feature Engineering

The model's raw inputs were processed before the training in order to clean and transform them. Bank-specific data was transformed into a table where each row corresponds to a particular bank and year; columns include all features and the next-year targets. Therefore, this assembled dataset contains the set of input features X and target outputs y needed for the ANN.

**Handling Missing Data:** In case of missing output features, that observation was excluded for training and prediction. In case of missing input features, it is preferable to employ a zero-imputation approach rather than imputing arbitrarily or dropping rows with any missing features, which would result in a reduction of usable data (Lekhansh, 2024; Van Ness & Udell, 2023). As a result, for each bank-year observation, if the target features were reported, the missing feature values were set to zero. Observations entirely lacking the P/B target or all features have been excluded.

**Feature Scaling (Standardization):** Input features were standardized as is best practice for ANNs, as features on different scales can negatively impact the training process. By scaling features to a common

scale, it is ensured that the optimization algorithm can make balanced weight updates for all inputs (*Feature Engineering: Scaling, Normalization, and Standardization*, 2025; Olamendy, 2025).
The scaler that performed best and was adapted in the final model is the StandardScaler which was applied on the training data.

$$X_{scaled} = \frac{x_i - x_{mean}}{\sigma}$$

The same scaling was applied to validation and test sets using the training parameters to avoid information leakage (Brownlee, 2020).

## 4.3 Model Architecture and Rationale

Due to the capability of ANNs to learn complex mappings from inputs to outputs with sufficient data, those have become a prominent model for financial forecasting and have been selected as the ML architecture in this study (Alkorbi et al., 2024; Huang et al., 2007; McInerney & Burke, 2024; Petropoulos et al., 2022). The ANN for this work was programmed in PyTorch and consists of an input layer matching the number of features, two hidden layers and an output layer with three neurons (one for each target). The hidden layers use fully connected neurons with ReLU as activation functions, which introduce nonlinearity while being efficient to train (Yadav, 2024).

In the process of optimization, the model parameters are iteratively adjusted to minimize a cost function measuring the difference between model predictions and actual values. For regression tasks an appropriate cost function is Mean Squared Error (MSE), calculated as the average squared difference between predicted and actual outcomes:

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^{2}$$

The optimizer adjusts the weights by calculating gradients to find the lowest point in the cost landscape. With the goal of improving the model's generalization and prevent overfitting, the two regularization methods Dropout and L2 weight decay were used. Dropout forces the network to not rely on any single neuron and encourages a more robust, distributed learning of patterns by randomly dropping X% of neurons during learning (Helmbold & Long, 2016; Salehin & Kang, 2023). A dropout rate of 0.3 was chosen based on common practices and trial-and-error, whereby an insufficient dropout rate results in overfitting and a rate that is too high leads to underfitting. Additionally, an L2 penalty (weight decay) was used, which adds an additional term to the cost function proportional to the squared magnitude of the model's weights:

$$\text{Regularized Cost} = MSE + \lambda \sum_{j=1}^{m} w_j^2$$

This L2 regularization, applied with a small coefficient ($1\times10^{-4}$), discourages overly large weights, thereby reducing the risk of fitting noise present in the training data (Connect et al., 1992). In essence, the combination of dropout and weight decay serves to constrain the model from memorizing noise in the training with the goal to improve its predictive performance on unseen data.

## 4.4 Training Procedure and Validation

The data dataset was split into three subsets (training, validation and test set) as recommended by Baheti (2021) and Jacob (2020). To maintain the data's chronological order and prevent information from leaking from the future to the past, the splits were made along the time dimension. The training period was from 2000 to 2016, the validation period was from 2017 to 2020 and the holdout test period was from 2021 to 2024, respectively. As a result, the model learns from data from the early 2000s to the mid-2010s, adjusts hyperparameters using data from the late 2010s and evaluates its performance using data from the most recent years. For replicating real-world forecasting scenarios, this splitting ensures the model is generating predictions on data from years that were not part of the training set.

The network was trained using the Adam optimizer (Adaptive Moment Estimation), a stochastic gradient descent method commonly used for neural networks (Agarwal, 2023; Kingma & Ba, 2015). The learning rate was set to 0.001 and the weight decay mentioned earlier was integrated into the Adam's parameter update. The model was trained for 500 epochs and the model parameters corresponding to the lowest validation MSE were retained as the final model. This procedure, which involves the utilization of a separate validation set with the purpose of monitoring performance, is an approach in ML to tune models while avoiding overfitting the test set.

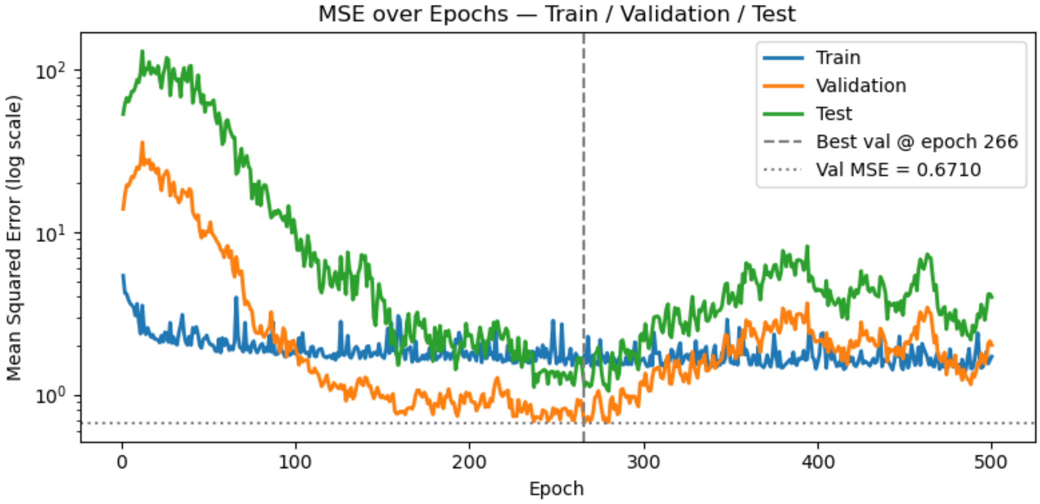
**Loss Function:** The network was trained to minimize MSE between the predicted and actual P/B values for the outputs in combination with the earlier detailed L2 regularization:

$$\mathcal{L}(\theta) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^{2} + \lambda \sum_{j=1}^{m} w_j^2$$

Ryll & Seidens (2019) showed that MSE is a common choice for regression problems as it directly penalizes prediction errors in a quadratic fashion. The three outputs were weighted equally to ensure that the error contributed by each P/B ratio was balanced.

**Optimization and Convergence:** Training and validation loss were monitored over the epochs, initially displaying a rapid decline, indicating that the network was capable of detecting the underlying signal. As seen in Figure 2, the MSE flattened out and started to slightly increase after a specific number of epochs (≈ 250), which is an indication for overfitting beyond that point. In Epoch 266, the final model with the lowest validation MSE was chosen.

*Figure 2: Training progress dynamics: MSE over epochs*




## 4.5 Model Evaluation

The model's performance was assessed on the test subset using multiple error metrics. The MSE and $R^2$ score were calculated for each of the three P/B ratios, while the Mean Absolute Error (MAE) was reported to provide more interpretable results, since MAE, expressed in raw percentage points, is more convenient to relate to actual valuation errors than the squared units of MSE. These evaluation metrics enable a practical assessment of the model's forecasting accuracy, both in absolute terms (how closely average predicted P/B values match actuals) and in relative terms (how well the model ranks banks by valuation).

As outlined in Table 3, the ANN achieved an $R^2$ of –2.8655, an MSE of 4.0885 and an MAE of 0.5343. The negative $R^2$ indicates that the model's predictive power on unseen data is worse than predicting the mean P/B. MSE penalizes large errors more than MAE does, therefore a higher MSE value indicates the occurrence of occasional severe prediction errors.

*Table 3: Overview of predictive accuracy of ANN*

| Time Delay | Architecture | Set | $R^2$ | MSE | MAE |
|---|---|---|---|---|---|
| 1 | 103-64-32-3 | Training | 0.7229 | 1.338995 | 0.474915 |
| 1 | 103-64-32-3 | Validation | -1.6747 | 2.065724 | 0.482364 |
| 1 | 103-64-32-3 | Test | -2.8655 | 4.088505 | 0.534258 |

Overall, the results show limited practical utility despite the use of a multi-layer architecture intended to capture the dynamics of financial data and complies with reviewed principles and best practices. The negative $R^2$ indicates poor generalization beyond the training dataset. Although MSE penalizes larger deviations more heavily, the MAE highlights that the forecasts deviate substantially from observed ratios. In essence, these findings indicate that forecasting reliable and concrete bank P/B multiples via a basic ANN approach is insufficient for producing reliable forecasts of P/B multiples.

# 5. Results

## 5.1 Model Output & Prediction Performance

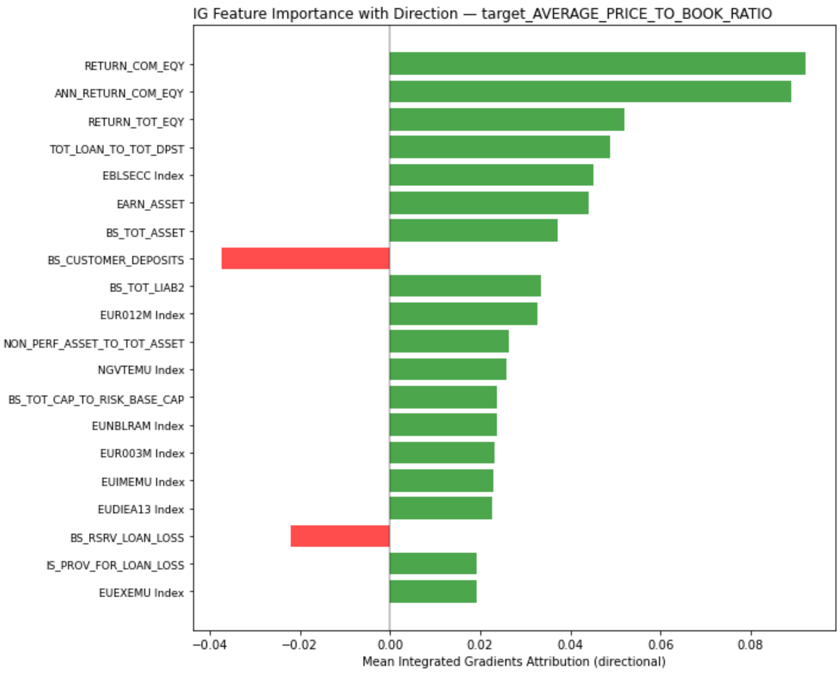
The ANN was trained on the previously described data and its predictive performance was evaluated using regression metrics. As shown in Table 3, the results indicate poor model accuracy. Specifically, the ANN's test-set $R^2$ was strongly negative (-2.87), accompanied by a high MSE of 4.09 and a large MAE of 0.53. The strongly negative $R^2$-value suggests that the model performed worse than simply predicting the average P/B-multiple for all valuations, exhibiting no reliable generalization beyond the training data.

From a practical perspective, the MAE of 0.53 is significant relative to the mean P/B multiple of banking institutions, which is 1.02. In summary, the model was unable to reliable predict P/B multiples, as evidenced by the error rates, which reduces its effectiveness in real-world valuation contexts. The failure of the model to reach a significantly positive measure of precision showcases the difficulties in employing an ANN to forecast valuation multiples. Overall, the error metrics indicate limitations of the model's predictive capabilities, which reduces its effectiveness in real-world valuation scenarios.

## 5.2 Feature Importance Analysis

An interpretability technique (Integrated Gradients) was applied to understand the model's predictions and to identify which input features most influenced the ANN's P/B-multiples output. Figure 3 illustrates the 20 most influential features driving the average price-to-book ratio prediction and indicate the direction of influence.

*Figure 3: Directional feature importance of average P/B-Multiple*




Across the average, high and low P/B targets, profitability metrics consistently emerged as the most significant and positively contributing factors. The detailed figures for high and low P/B are presented in Appendix A.2 and A.3, respectively. ROE and its variations demonstrated particularly significant positive impact on the predicted P/B. These results suggest that the model has learned to associate higher profitability with higher valuation multiples, a principle that aligns with fundamental valuation intuition and prior studies (higher ROE generally supports a higher P/B, all else being equal). The ANN's behavior indicates that banks with higher equity base profits were expected to have higher P/B ratios, which reflects investors' tendencies to pay a premium for profitability and prior research on bank valuation (Chen & Zhang, 2002; Dayag & Trinidad, 2019; Yin et al., 2014), which also identifies profitability as a key driver for determining intrinsic value.

In contrast, features related to asset quality and funding structure negatively affected the model's P/B prediction. Notably, a high reserve for loan losses (e.g. loan-loss provisions and reserves) where associated with a lower forecasted P/B ratio. This suggests that the model interprets significant credit loss reserves as an indicator of lower asset quality or anticipated future losses and therefore considers them to be a factor that reduces a bank's valuation. Similarly, customer deposits were identified to negatively impact the predicted P/B multiple. A large deposit base can generally be considered a strength but according to the ANN it appears to function as an indicator of excess funding that is not being converted into earning assets and a low loan-to-deposit usage, which results in a lower overall valuation.

The ANN appears to penalize banking institutions that exhibit signs of asset-quality issues or underutilized liquidity, consequently assigning them lower valuation multiples. The model identifies negative drivers which highlight traditional concerns in bank valuation. For instance, elevated levels of loan loss provisions can result in discounted P/B multiples due to the fact that these elements may serve as indicators for risk and potential future losses (Sukmadewi, 2020). The Integrated Gradients analysis of the model indicates its ability to identify reasonable economic relationships, such as rewarding strong earnings and penalizing credit risks, despite the model's overall poor predictive accuracy.

Across all forecasted P/B multiples ROE and related profitability indicators consistently ranked as the most influential factors, underscoring profitability as a primary driver in the valuation of banks. However, there were some nuanced differences in feature influence between the scenarios. For the low P/B multiple, the Tier 1 Capital Ratio emerged as one of the 20 most influential features, indicating that capital adequacy became more significant. This finding indicates that, in predicting the potential downside valuation, the model considered a strong capital buffer as a mitigating factor.

Conversely, within the high P/B scenario, certain macroeconomic indicators exhibited a slightly greater presence. Specifically, the model incorporated a slightly larger weight on the 12-month Euribor when determining the upper-bound P/B. This suggests that a higher valuation multiple could be a result of a positive macroeconomic climate or bullish market conditions. This conclusion is reasonable as bank earnings and investor optimism are typically supported by robust economic growth and declining interest rates. However, those macroeconomic factors were found to be of secondary importance when compared to core financial metrics, as all valuation models were influenced by the same primary factors of asset quality and profitability.

The concept of certain financial ratios, particularly ROE, being universally important in bank valuation is reinforced by existing literature (Amiputra et al., 2021; Bogdanova et al., 2018; Chen & Zhang, 2002). In summary, the feature importance analysis indicates that the model was successful in the identification of key determinants in valuation, despite its limited capabilities in accurately predicting the P/B.

## 5.3 Comparison to Traditional Equity Valuation

The traditional valuation of Banco CTT, conducted as part of the valuation of the CTT group, combined price/tangible book value (P/TBV) multiples from peer transactions and a DCF model. Incorporating assumptions on macroeconomic trends, modeling loan-loss provisions, capital buffers, efficiency gains and other relevant factors, the equity value of Banco CTT was estimated at EUR 153M. The traditional model produced a P/B multiple of 0.52 at a Book Value of EUR 296M. The complete conceptual and quantitative framework of the traditional approach is documented in detail for the interested reader in Appendix B, where a full description of the underlying financial data, modelling assumptions and step-by-step valuation mechanics is provided.

These results indicate that the Banco CTT valuation from the traditional model lies outside of the bounds predicted by the ANN model, with a P/B multiple range of 0.65 to 1.05. However, this discrepancy does not necessarily undermine the reliability of the traditional valuation method. The DCF valuation incorporates explicit forward-looking assumptions regarding the evolution of loan mixes, regulatory dynamics and expenses related to digital platforms, which lie beyond the scope of last year's accounting figures. In contrast, the ANN extrapolates exclusively from historical patterns, which limits the capabilities of anticipating strategic shifts that potentially lack precedent in the training data.

Moreover, the performance of the ANN of an $R^2$ of -2.87 and a MAE of 0.53 across the entire test set, suggests that the proximity to the Banco CTT valuation is a statistical coincidence rather than a result of systematical accuracy. Additionally, the absence of contextual information restricts the effective utilization of the ANN.

It has been established that both approaches identify profitability, asset-quality provisioning and capital strength as the major factors influencing a company's value. This finding aligns with the established relationship between ROE and P/B in the context of bank valuation theory. However, it is only through the application of human expertise that these drivers can be transformed into a justifiable and discussable multiple based on cash-flow forecasts and peer-market triangulation, an approach that the ANN is not currently capable of.

## 5.4 Discussion

The findings of this study demonstrate that an ANN trained solely on historical balance-sheet and macroeconomic data is ineffective at producing a consistent intrinsic valuation for financial services companies. The test-set performance of the ANN is inferior to that of a simple mean predictor ($R^2 = -2.87$) and the MAE of 0.53 is quantitatively significant. A negative $R^2$ indicates that the model introduces noise rather than explanatory power, which is an indication of over-fitting and out-of-distribution weakness. However, the integrated-gradient analysis confirms that the network has obtained the same primary drivers of financial value as traditional valuation, which are essential for bank valuation. Specifically, the effects of a high ROE increasing the P/B, while loan-loss reserves, inadequate capital and surplus liquidity negatively impact the P/B ratio. These findings are consistent with existing literature on the relationship between ROE and P/B in the context of the valuation of banks.

In summary only part of the research question can be affirmatively addressed by the convergence on important drivers of bank valuation, demonstrating that an ANN is capable of recognizing the same key determinants used in conventional equity research. However, an ANN trained on historical bank fundamentals and macroeconomic data remains insufficient for accurate intrinsic bank valuation, failing to outperform a naive benchmark and thus negatively answering the research question overall.

As shown in Table 4, both traditional and ML-based valuations consistently identify profitability and risk as key drivers, reflecting the established ROE & P/B connection in valuation. However, the approaches differ in the ways they process these drivers, as the traditional method incorporates those in forward-looking cash-flow forecasts and market cross-checks, whereas the ANN relies solely on observed historical patterns and ultimately fails to extrapolate a valuation trajectory or identify qualitative differentiators.

*Table 4: Comparison of Traditional Valuation vs. ANN-based Valuation*

| | **Traditional FCFE Valuation** | **ANN-Based Valuation** |
|---|---|---|
| **Approach** | Forward-looking FCFE forecast (2024-2029) + P/TBV cross-check; explicit macro, credit-quality and strategic assumptions | Pattern recognition on historical financial & macro variables; no explicit forecasts or qualitative inputs |
| **Key Drivers Identified** | ROE, loan-loss provisions, capital ratios, cost-to-income efficiency | Same variables emerge as top Integrated-Gradient features (positive: ROE; negative: reserves, deposits) |
| **Implied P/B Multiple for Banco CTT** | =0.56 P/B | Estimate unreliable ($R^2 < 0$; MAE=0.53); not decision-usable |
| **Strengths** | Incorporates bank-specific strategy, regulatory guidance, scenario analysis | Rapid, unbiased scan of ~100 quantitative features; highlights fundamental ROE-P/B link |
| **Limitations** | Subjective assumptions, labour-intensive, limited scalability | Lacks forward-looking context; fails on capturing specific nuances |

These findings suggest that a hybrid workflow may be a viable way forward by using ML to find and measure the drivers across a large peer group and in a subsequent step applying expert judgment to incorporate those drivers into cash-flow projections and multiples. This methodology would incorporate the advantages of both approaches by leveraging the contextual depth that only human expertise can offer, while maintaining the scale and objectivity of data-driven analysis. This integrative approach is currently being explored by Cao et al. (2024), with the results indicating its potential effectiveness so far.

# 6. Conclusion

This study aimed at determining whether a machine-learning model trained exclusively on publicly available financial statements and macroeconomic indicators can generate a credible stand-alone valuation for a previously unpriced bank. In doing so, it is also designed to allow for the possibility to compare the valuation drivers uncovered by the algorithm with those employed in conventional analyst practice. Utilizing a dataset of 5,088 firm-year observations of 415 European banks over the period from 1999 to 2024, an ANN was designed to predict forward P/B multiples. The network was configured with a chronological train-validation-test split and the implementation of standardization, dropout and weight-decay regularization was selected to align with best practices in both finance and data science. The performance was benchmarked against the test set containing the data from 2021 to 2024.

The findings provide a clear outcome, on the hold-out test set the neural network showed a strongly negative $R^2$ (-2.87) and a MAE of 0.53, indicating it performed worse than a naive strategy of forecasting the mean P/B multiple. In summary, the algorithm was unable to convert historical balance-sheet patterns into valuation estimates that were sufficiently precise for practical use. Nonetheless, the interpretability analysis revealed the model's ability to consistently place the most weight on profitability, followed by asset-quality measures and capital adequacy. These dimensions correspond to relevant determinants of traditional bank valuation frameworks. Thus, while the network proved inconsistent in its ability to forecast prices, it demonstrated a logical correlation between financial characteristics and valuation outcomes.

These findings offer a nuanced response to the guiding research question. A neural network does not yet provide reliable stand-alone intrinsic valuations for an unlisted or newly listed bank; professional standards for producing credible stand-alone bank valuations are not being met. At the same time, model's attribution profile converges on the main value drivers emphasized in traditional analysis, confirming that algorithmic pattern recognition can replicate established valuation logic even if it lacks the ability to transform the logic in combination with the dataset into precise price estimates. The comparison between the traditional and the ANN valuation surfaces complementary strengths and weaknesses. The analyst-led DCF benefits from forward-looking projections, regulatory insight and qualitative judgement, but is susceptible to assumption risk and behavioral bias. In contrast, the ANN operates at scale with objectivity and speed; yet its inability to account for strategic context, policy shifts and uncommon events leaves it exposed to errors. These contrasts indicate that considering an ANN as substitution would be premature, whereas a symbiosis of both approaches, leveraging their respective strengths, may be a promising path forward.

For practitioners the implication of these findings is that ML, while not yet capable of replacing traditional valuation models, can enhance those as a form of decision-support. The ANN has been shown to identify the key indicators of bank value that analysts monitor, such as profitability, asset quality and capital strength. This capability enables the network to scan peer universes and highlight institutions with financial profiles that significantly deviate from these established drivers. This possible form of a "pre-analysis" has the potential to yield practical benefits. The trained network can function as a prioritization engine by quantifying the marginal contribution of each variable to the predicted P/B. The ANN is capable of identifying the subset of financial ratios that account for the bulk of a valuation, thereby directing analysts' effort toward the most economically consequential drivers in their analysis. Furthermore, the model's capabilities function as a data-sufficiency diagnostic. The proportion of variance that the model is capable of explaining with the available disclosures provides an indication of the adequacy of the current information set. If the explanatory value is low, this suggests that additional forward-looking or qualitative inputs are required before a valuation is performed. The combined use of these applications demonstrates how ML can enhance, rather than substitute, traditional analyst assessment.

Nonetheless, several limitations frame the conclusions of this study. The input space was limited to annual accounting data and the set of macroeconomic variables, not considering forward-earnings guidance, text-based sentiment and intra-year market signals. Furthermore, the analysis focused exclusively on ANN architectures, thereby excluding alternative structures, such as graph or recurrent networks, which have the potential to capture temporal dependence and inter-bank linkages. Finally, the study did not assess a hybrid workflow, consisting of human and AI, leaving the potential incremental contribution of machine insight to an analyst's valuation as an area for future research.

Consequently, future research should aim to expand the available information set and the range methodological approaches. The incorporation of forward-looking disclosures, real-time risk indicators and sentiment measures could potentially provide the context that the accounting series lack. The implementation of graph-based models to represent balance-sheet interconnectedness, or the utilization of ensembles that combine heterogeneous learners, has the potential to enhance predictive power. Most critically, valuation processes could benefit from pragmatic hybrid approaches in which algorithms screen peer universes, quantify key drivers and flag anomalies, while analysts supply scenario logic, regulatory guidance and narrative coherence.

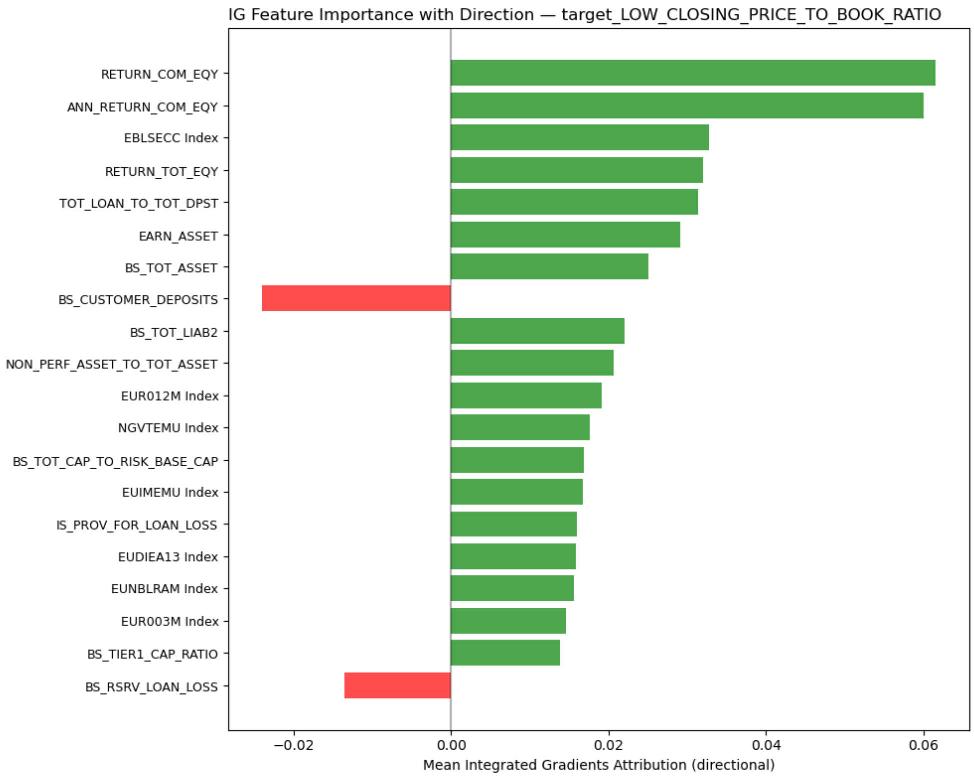
## Appendices

# Appendix A: ANN Valuation

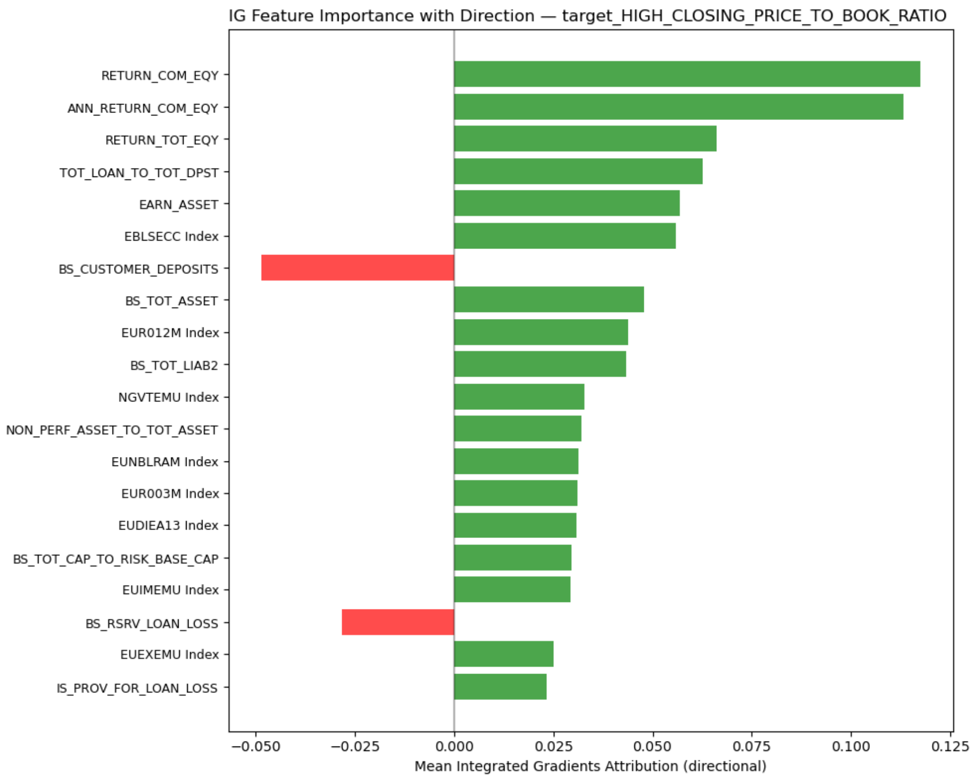
## Appendix A.1: Overview Bank Variables and Bloomberg Code incl. Description

| Feature Name | Bloomberg Code | Brief Explanation | Category |
|---|---|---|---|
| Annualized Net Interest Margin | ANN_NET_INT_MARGIN | Net return on bank's earning assets, annualized | Profitability |
| Annualized Return on Common Equity | ANN_RETURN_COM_EQY | Annualized profit relative to common shareholders' equity | Profitability |
| Annualized Return on Assets | ANN_RETURN_ON_ASSET | Annualized profit relative to average total assets | Profitability |
| Book Value per Share | BOOK_VAL_PER_SH | Total common equity divided by shares outstanding | Capital Adequacy |
| Basel Level Adopted Indicator | BS_BASEL_LEVEL_ADOPTED_INDICATOR | Indicates Basel framework level adopted by bank (e.g., Basel III) | Capital Adequacy |
| Total Deposits | BS_CUSTOMER_DEPOSITS | Total deposits received from customers | Liquidity & Funding |
| Net Loans & Mortgages | BS_LOAN_MTG | Loans and mortgages, net of reserves for loan losses | Asset Quality |
| Non-Performing Assets | BS_NON_PERFORM_ASSET | Assets not accruing interest or not being paid (loans, foreclosed real estate, etc.) | Asset Quality |
| Risk-Weighted Assets | BS_RISK_WEIGHTED_ASSETS | Assets weighted by risk, used in capital adequacy calculations | Capital Adequacy |
| Reserve for Loan Losses | BS_RSRV_LOAN_LOSS | Reserve established to cover probable loan losses | Asset Quality |
| Tier 1 Capital Ratio | BS_TIER1_CAP_RATIO | Core capital to risk-weighted assets | Capital Adequacy |
| Total Assets | BS_TOT_ASSET | Sum of all short and long-term assets | Asset Quality |
| Total Capital Funds | BS_TOT_CAP_FUND | Total regulatory capital (Tier 1 + Tier 2) | Capital Adequacy |
| Total Risk-Based Capital Ratio | BS_TOT_CAP_TO_RISK_BASE_CAP | Total capital to risk-weighted assets (CAR) | Capital Adequacy |
| Total Liabilities | BS_TOT_LIAB2 | Sum of all current and non-current liabilities | Liquidity & Funding |
| Total Loans | BS_TOT_LOAN | Gross loans (commercial, consumer, other) | Asset Quality |
| Cash from Financing Activities | CF_CASH_FROM_FNC_ACT | Net cash from issuing debt, equity, or paying dividends | Liquidity & Funding |
| Cash from Investing Activities | CF_CASH_FROM_INV_ACT | Net cash from purchase/sale of assets, investments | Liquidity & Funding |
| Cash from Operations | CF_CASH_FROM_OPER | Net cash generated by operating activities | Liquidity & Funding |
| Net Change in Cash | CF_NET_CHNG_CASH | Net change in cash and equivalents | Liquidity & Funding |
| Earning Assets | EARN_ASSET | Income-producing assets (loans, investments, etc.) | Asset Quality |
| Net Income Available to Common | EARN_FOR_COMMON | Net income after preferred dividends and other adjustments | Profitability |
| Efficiency Ratio | EFF_RATIO | Operating expenses as a percentage of revenue | Operational Efficiency |
| Effective Tax Rate | EFF_TAX_RATE | Total tax paid as a percentage of pretax income | Profitability |
| Diluted EPS | IS_DILUTED_EPS | Earnings per share, including dilutive securities | Profitability |
| Diluted EPS from Continuing Ops | IS_DIL_EPS_CONT_OPS | Diluted EPS from continuing operations | Profitability |
| Basic Earnings per Share | IS_EPS | Earnings per share, basic | Profitability |
| Operating Income or Losses | IS_OPER_INC | Revenue minus operating expenses | Profitability |
| Personnel Expenses | IS_PERSONNEL_EXP | Wages, salaries, benefits, excluding directors' emoluments | Operational Efficiency |
| Provision for Loan Losses | IS_PROV_FOR_LOAN_LOSS | Expense for possible future loan losses | Asset Quality |
| Loan Loss Reserve to Non-Perf Assets | LOAN_LOSS_RES_TO_NON_PERF_ASSET | Reserve for loan losses as a percentage of non-performing assets | Asset Quality |
| Net Income to Common Margin | NET_INCOME_TO_COMMON_MARGIN | Net income available to common shareholders as a percentage of revenue | Profitability |
| Net Interest Income | NET_INT_INC | Interest income minus interest expense | Profitability |
| Net Interest Spread | NET_INT_SPREAD | Interest yield on assets minus rate paid on liabilities | Profitability |
| Net Revenue | NET_REV | Sum of interest income, trading profits, commissions, minus interest expense | Profitability |
| Net Revenue (Net of Commissions Paid) | NET_REV_EXCL_COMMISSIONS_PAID | Net revenue minus commissions paid | Profitability |
| Net Revenue Growth | NET_REV_GROWTH | Year-over-year growth in net revenue | Growth |
| Non-Interest Expense | NON_INT_EXP | All expenses except interest | Operational Efficiency |
| Non-Interest Income | NON_INT_INC | Income from sources other than interest (fees, trading, etc.) | Profitability |
| Non-Perf Assets to Total Loans | NON_PERFORM_ASSET_TO_TOT_LOAN | Non-performing assets as a percentage of total loans | Asset Quality |
| Non-Perf Assets to Total Assets | NON_PERF_ASSET_TO_TOT_ASSET | Non-performing assets as a percentage of total assets | Asset Quality |
| Operating Margin | OPER_MARGIN | Operating income as a percentage of revenue | Profitability |
| Pretax Margin | PRETAX_MARGIN | Pretax income as a percentage of revenue | Profitability |
| Pre-Tax Pre-Provision Profit to Net Revenue | PRETX_PREPROV_PROF_TO_NET_REV | Profit before provisions and taxes as a percentage of net revenue | Profitability |
| Pre-Tax Pre-Provision Profit | PRE_TAX_PRE_PROVISION_PROFIT | Profit before provisions and taxes | Profitability |
| Profit Margin | PROF_MARGIN | Net income as a percentage of revenue | Profitability |
| Provision for Loan Loss to Total Loans | PROV_FOR_LOAN_LOSS_TO_TOT_LOAN | Provision for loan losses as a percentage of average total loans | Asset Quality |
| Return on Assets | RETURN_ON_ASSET | Net income as a percentage of average total assets | Profitability |
| Return on Total Equity (Including Pref.) | RETURN_TOT_EQY | Net income as a percentage of average total equity | Profitability |
| Reserve for Loan Loss to Total Loans | RSRV_FOR_LOAN_LOSS_TO_TOT_LOAN | Reserve for loan losses as a percentage of total loans | Asset Quality |
| Sustainable Growth Rate | SUSTAIN_GROWTH_RT | How much a firm can grow without borrowing more money | Growth |
| 12-Month Net Interest Margin | T12_NET_INT_MARGIN | Net interest margin over trailing 12 months | Profitability |
| Tangible Common Equity | TANGIBLE_COMMON_EQUITY | Common equity minus intangible assets | Capital Adequacy |
| Tangible Book Value per Share | TANG_BOOK_VAL_PER_SH | Tangible common equity divided by shares outstanding | Capital Adequacy |
| Tangible Common Equity Ratio | TCE_RATIO | Tangible common equity as a percentage of tangible assets | Capital Adequacy |
| Tangible Common Equity to Risk-Weighted Assets | TCE_TO_RWA | Tangible common equity as a percentage of risk-weighted assets | Capital Adequacy |
| Total Equity | TOTAL_EQUITY | Total assets minus total liabilities | Capital Adequacy |
| Total Common Equity | TOT_COMMON_EQY | The amount all common shareholders have invested | Capital Adequacy |
| Total Loans to Total Assets | TOT_LOAN_TO_TOT_ASSET | Loans as a percentage of total assets | Asset Quality |
| Total Loans to Total Deposits | TOT_LOAN_TO_TOT_DPST | Loans as a percentage of total deposits | Liquidity & Funding |

## Appendix A.2: Directional Feature Importance Analysis Low P/B




## Appendix A.3: Directional Feature Importance Analysis High P/B

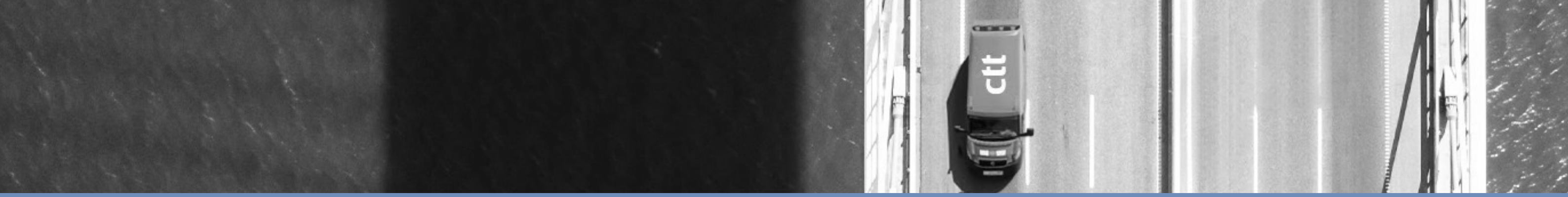


# Appendix A.4: ANN-Model Setup in PyTorch

```
class NeuralNetwork(nn.Module):

    def __init__(
        self,
        n_inputs:      int = len(input_cols),
        hidden_dims:   list[int] = (64, 32),
        dropout:       float   = 0.3,
        n_targets:     int     = len(target_ratios)
    ):
        super().__init__()
        self.time_delay = 1
        mlp_input_dim = n_inputs
        layer_dims     = [mlp_input_dim, *hidden_dims, n_targets]
        self.structure = "-".join(str(d) for d in layer_dims)

        layers = []
        in_dim = mlp_input_dim
        for h in hidden_dims:
            layers += [
                nn.Linear(in_dim, h),
                nn.ReLU(inplace=True),
                nn.Dropout(dropout),
            ]
            in_dim = h

        # Final linear + Softplus so output > 0
        layers.append(nn.Linear(in_dim, n_targets))
        #layers.append(nn.Softplus()) <-- Greyed out for now - no softplus activation

        self.mlp = nn.Sequential(*layers)

    def forward(self, values_t: torch.FloatTensor) -> torch.FloatTensor:
        return self.mlp(values_t)      # shape = (batch, n_targets), all > 0
```

# Appendix B: Equity Research Report CTT Group (Traditional Valuation)

The main work can be read independently of this part of the Appendix, although it provides a better understanding of the analysis, as it the part in which the traditional valuation of Banco CTT was performed. The valuation of other segments of CTT are outside the scope of this MFW, as it aims to provide a new perspective on valuation for the banking segment, specifically the possibility of valuing it using an ANN vs. traditional valuation techniques.






# Between Promise and Doubt: A Hold Stance on CTT

## Investment Summary

HOLD is the recommendation for CTT – Correios de Portugal, SA with a price target of €5.8/sh for 2025YE using a DCF model, with a Sum-of-the-Parts (SoP) approach. Our forecast implies a 7.7% upside from the June 27th, 2025, closing price of €5.4/sh, with a medium risk. Despite the timid upside, additional value can be unlocked with recent transactions beyond our base case. Our recommendation is based on the following pillars: (i) notable Courier, Express, and Parcel (CEP) potential from Iberia, (ii) the declining nature of the traditional yet regulated Mail business, (iii) uncertainty surrounding cost reduction strategies and the diversification impact of Banco CTT and Financial Services segments.

**Table 5: Investment Recommendation**

| CTT Group Equity Value | €k | €/sh. |
|---|---|---|
| **Equity Value by Segment** | | |
| Logistics (Mail + Express & Parcels) | 404,522 | 3.00 |
| Financial Services | 217,957 | 1.61 |
| Real Estate (73.7% stake) | 113,086 | 0.84 |
| Banco CTT (91% stake) | 134,788 | 1.00 |
| Adjustments | -187,343 | -1.39 |
| Expected Net Value from the acquisitions | 97,524 | 0.72 |
| **Estimated Equity Value** | **780,535** | **5.78** |
| Current Equity Value | 724,836 | 5.37 |
| Upside / Downside | 7.7% | 0.00 |
| **Recommendation** | **HOLD** | |

*Source: Team Estimates*

**Building on Tradition: CTT's Brand as USP**

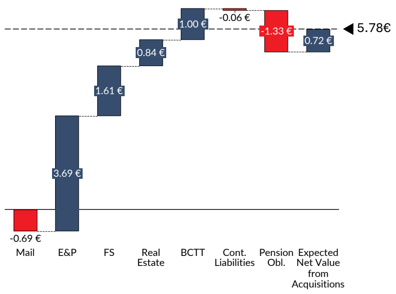
The century-long history of CTT, along with its presence and extensive reach in Portugal (2,375 access points, 569 post offices, 1,806 postal agencies, 5,063 Pay Shop agents 23YE) is the Group's major asset. Building on the trust established over such a long period, the company has expanded its business portfolio from traditional mail to financial services, making Banco CTT an important mark.

**CTT wants to focus on packages, not on the Bank**

The growth potential of Banco CTT remains limited due to the constrained nature of its loan portfolio expansion. Additionally, the rise of FinTech competitors, known for their innovation, agility, and speed, poses a significant challenge to CTT's established trust and loyal customer base. CTT's management has conveyed a clear strategic direction: the primary focus will be on the packages segment, while Banco CTT may become a target for acquisitions or a potential spinoff in the future. Generali acquired an 8.7% stake in Banco CTT in November 2024 as part of a strategic partnership with CTT Group.

**Group Valuation Methods |** A DCF model based on SoP FCFE applying different cost of equity per segment was used and reached a €5.8/sh price target.

**Figure 4: Price Target Distribution**




*Source: Team Estimates*

**Banco CTT Traditional Valuation**

€153M equity valuation (0.52x P/B) for Banco CTT from a FCFE DCF model with the following key drivers:

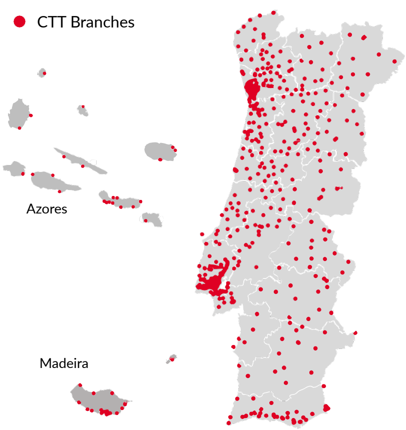
***Revenue Drivers:*** NII grows at 3.1% CAGR (2024-29), driven by auto loan securitization (+18% YoY FY23) offsetting compression of margins in mortage loans (€10.5M by FY29) from Euribor normalization. Non-interest revenue expands at 2.9% CAGR through Generali partnership fees and cross-selling.

***Capital & Profitability:*** CET1 ratio strengthens to 22.5% (2029) from 20.7% (2023), prioritizing regulatory buffers over ROE enhancement (4.1% FY29E). This reflects management's current hypothesis on future for banking segment in CTT Group. Cost-to-income remains above peers (60% vs sector avg 38.3%) due to future investments in IT and digitalization.

***Risk Assumptions***: Cost of equity set at 9.44% (German 10Y bond 2.20% + Portuguese MRP 5.86% + CRP 1.38%). Terminal growth rate is set at long-term Portugal's GDP growth of 2%.

**Risk to the Price Target |** Buying the stock yields several risks, CTT has a differentiated portfolio comprehensive of: (i) a stable Revenues (CAGR25-29 0.3%) yet unprofitable Mail business (-1% EBIT Margin FY24 and reaching -5% FY29) which poses challenges in terms future sustainability; (ii) an expanding E&P segment (CAGR25-29 +12% Revenues and 19% EBIT Margin including the anticipated CACESA acquisition and DHL JV). Besides offering notable room for growth, the Courier Industry also poses challenges in terms of competitiveness, exacerbated by the integration after the future acquisition. Competition is also relevant for (iii) the FS and (iv) Banco CTT along with the exposure to market conditions.

**Figure 5: CTT Branches in Portugal**



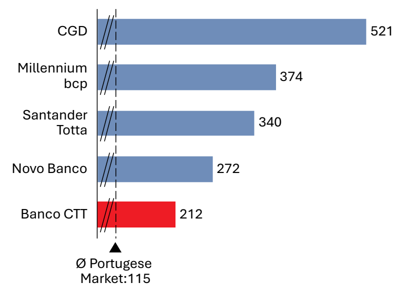

*Source: CTT Annual Reports*

## Business Description

CTT – Correios de Portugal is a Portuguese logistics operator, primarily focused on the deliveries of mail, parcels, and with complementary businesses in the financial services industry. Founded in 1520 by King Manuel I of Portugal, the company operates in the Iberian Peninsula. In 2016 the company started to enter the financial services sector thanks to its solid footprint in Portugal with 569 physical locations, founding Banco CTT (currently in 212 branches). (Figure 5)

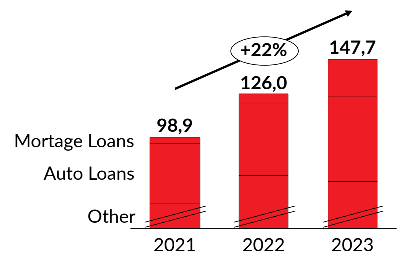
CTT is expected to report €985M Revenues FY23 (+5% YoY) and is expected to reach €1,012M by 2024YE. The group is divided into 4 business units (BUs) – Mail & Other (44% 24YE Sales, -3% 24YE recurring EBIT €-3.3M), Express & Parcels (E&P) (35%, 23% | €20M), Financial Services (6%, 42% | €36M) and Banking (15%, 29% | €25M).

**Figure 6: No. of Bank Branches in PT**



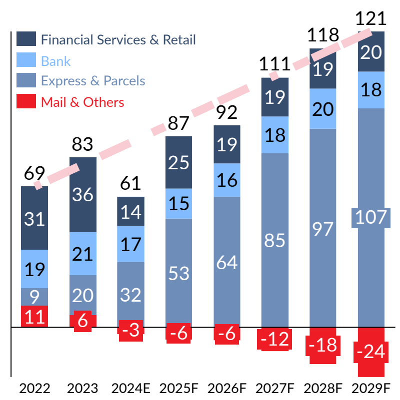

*Source: Portuguese Banking Association*

**Figure 9: Banco CTT Revenues in €M**



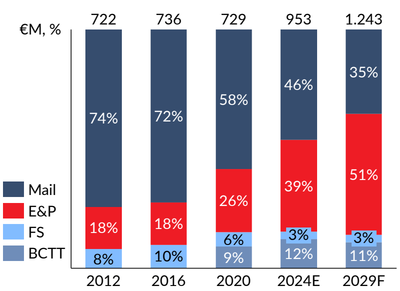

*Source: CTT Annual Reports*

**Figure 10: EBITDA per Segment in €M**




*Source: Team Estimates*

**Figure 11: Revenues per Segment in €M**




*Source: Team Estimates*

Digitalization and sustainability are two trends impacting CTT. Digitalization yielded declining mail volumes in the Mail & Other BU, while the expansion in e-commerce created room for long-term growth in E&P. Recognizing the current situation, management sought alternative business strategies, ultimately focusing on the Courier, Express, and Parcel (CEP) business. Moreover, the growing importance of sustainability to investors is leading E-sellers to prioritize green fleet companies for last-mile deliveries and sustainable products for purchasing to accommodate customers.

**Banco CTT |** As part of the company's expansion into the financial sector, BCTT was established in March 2016. Auto loans (34%) and mortgage loans (33%) make up the majority of BCTT's retail banking offerings. It is a subsidiary of CTT (which currently holds 91%), with the remaining 9% owned by Generali since 2024. One of CTT's competitive advantages is the usage the vast postal network of the CTT Group, which consists of more than 500 branches across Portugal.

With a revenue of €148M (+17% YoY), BCTT's FY23 performance demonstrated notable revenue growth. The main driver of this growth was the increase in net interest income, which came to €99M (+33% YoY). The Interest rate increases had a significant impact on the performance, as the bank was able to benefit from the securitization of auto loans and higher returns on customer deposits.

A major component of BCTT's operations is the auto loan portfolio, which generated €53M in interest income, representing an 18% YoY growth and a 13% total increase in the loan portfolio net of impairments.

With interest income from mortgage loans reaching €23M, a 315% increase over the previous year, BCTT expanded in the mortgage sector. This rise is the result from a combination of variable interest rates on mortgage loans and rising Euribor rates, significantly boosting the bank's returns on the growing mortgage portfolio, valued at €727M as of 23YE.

In the future, BCTT aims to continue its growth, with ambitious goals set for FY25, including expanding its customer base to c. 700k and accounts to c. 750k (vs. 647k in FY23), increasing total customer resources and loans to over €7bn, and as a result achieving pre-tax profits between €25M and €30M.

**Other Corporate Group Segments**

**Mail and Other |** This segment accounts for 44% of total group sales. With over 2,300 access points, it manages most of Portugal's postal traffic. However, mail volumes declined in FY23, with a 39% drop in unaddressed mail and an 8% drop in addressed mail. Because pricing is controlled, revenues remain steady, but overall profitability is decreasing.

**Express & Parcels (E&P) |** Representing 35% of total sales, this segment focuses on B2C last-mile delivery in Portugal and Spain. The profitability improved to a 5% EBIT margin in FY23, and E&P revenues rose 31% to €341 million. Improving e-commerce logistics and expanding the company's footprint in the Iberian market are the goals of recent partnerships and acquisitions, e.g. the one with DHL and the Spanish company CACESA.

**Financial Services (FS) |** Despite only making up 6% of total group revenues, the segment generates the strongest profitability with EBIT margins above 45%. The segment consists of retail goods, insurance products offered through a partnership with Generali, and savings products. Revenues had increased gradually because of a rising number of sales of insurance products and government savings certificates.

**Real Estate Management |** In May of 2023, CTT launched its subsidiary CTT IMO Yield, in collaboration with Sonae Sierra. The joint venture aims to fully capture the value of CTT's real estate portfolio by optimizing different factors like better space utilization, attracting new tenants, and exploring expansion opportunities. Additionally, in January of 2024, the sale of 26.3% of CTT IMO Yield to SONAE Investments and other investors was completed.

**Strategic Direction**

**Leveraging Infrastructure for Sustainable Growth |** CTT's profitability hinges significantly on the shared use of its infrastructure, primarily built around the Mail segment but leveraged across all business units. This integration allows segments like E&P, FS, and BCTT to benefit from economies of scale while operating costs are predominantly booked under the Mail segment. Although mail volumes are steadily declining, regulated price adjustments have mitigated revenue loss, enabling a smoother transition to diversified business activities. This shared infrastructure underpins cost efficiency and supports profitability across the Group, as the Mail segment absorbs most of the fixed operational costs funded from regulated activity.

**Possible Separation of Banco CTT from Group |** Management at CTT has voiced the possibility of reducing exposure to Banco CTT through a potential spin-off or IPO. CEO João Bento explicitly stated that CTT is not the ideal shareholder for a bank, emphasizing that the company's capital allocation priorities in the future will be more focused on the Iberian parcels expansion (CACESA acquisition, DHL JV). This change aims to address two issues CTT currently is faced with:

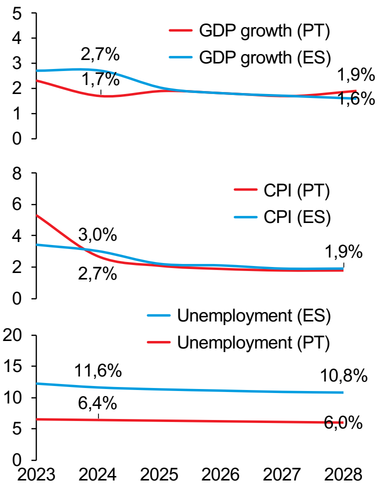
*Capital efficiency:* Banco CTT would require capital investments in order to compete, whereas CTT's capital would be better deployed towards high-return logistics opportunities (the target is to increase E&P revenue by 35% by FY26). Divesting banking exposure could redirect over €120M allocated for bank digitalization towards strategic projects for E&P in the Iberia.

*Investor engagement:* The current conglomerate structure potentially discourages specialized investors, as logistics-focused funds avoid banking risk, while financial investors may seek pure-play institutions. A separation can resolve this mismatch and increase CTT's standalone valuation (currently discounted by 15–20% compared to peers).

# Industry Overview and Competitive Positioning

**Iberian Economic Outlook**

Figure 12: Macroeconomic Indicators




*Source: EIU Estimates*

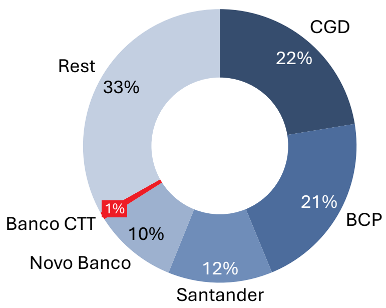
Portugal's economic growth is expected to be at 1.7% (2.7% ES) in 2024 before rebounding to 1.9% (1.6% ES) in 2025, according to EIU. This growth is expected to be mostly driven by private consumption and investments. Inflation is forecasted to ease to a level of 2.7% (3.0% ES) in 2024 and 1.9% (2.3% ES) in 2025, while unemployment will remain stable over the entire period. In 2023, rising interest rates increased net interest margins for banks but on the other hand reduced consumer demand for credit. BCTT saw strong growth in customer deposits (+36.0%) and mortgage loans (+10.5%) during this period. However, the higher cost of borrowing poses risks to future loan demand, as households may become more cautious about taking on new debt. Despite having a stable domestic outlook, external geopolitical risks remain a challenge causing uncertainty and are possible risks for growth and inflation outlooks.

**Geopolitical Instability**

The global context has been marked by a significant degree of uncertainty in recent years and continues to be so at present. The war in Ukraine and tensions in the Middle East are concerning developments that could lead to economic slowdowns and geopolitical instability. The main effects of this instability are the consequent reactions of central banks to monetary policy and possible disruptions to the global supply chain. These effects significantly impact the Group BUs and their revenue generation capacity. In addition to uncertain economic spillovers from U.S. actions, current political uncertainty in Europe poses another layer of volatility to economic growth.

**Financial Service Providers Market Overview**

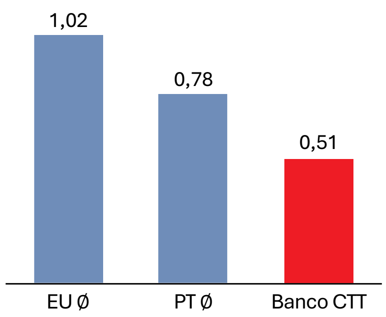
Figure 13: Banks Market Share in PT




*Source: Portuguese Banking Association*

**Overall Portuguese Banking Market |** The Portuguese banking industry continues to be competitive despite the financial stability risks from geopolitical tensions and tight monetary conditions. Players like Caixa Geral de Depositos (CGD), Banco Comercial Português (BCP), Banco Santander Totta, and Novo Banco are the big 4 commercial banks that dominate the majority of the market. BCTT focuses on retail and digital banking strategies, leveraging CTT's postal network to deliver accessible banking services, especially to underserved areas. Although this provides a unique position, rural regions are less profitable, therefore BCTT is still exposed to growing competition from more established banks, fintech, and digital banking players in urban markets.

Figure 14: Loan-to-Deposit Ratios



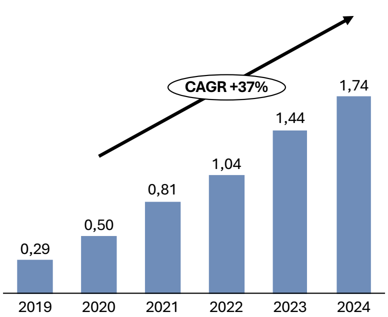

*Source: ECB Data, BPStat, Team Estimates*

**Liquidity and Solvency |** In 2023, the Portuguese Banking Sector demonstrated robust liquidity, with a loan-to-deposit ratio of 78% reflecting cautious lending. BCTT, like other banks, maintained strong liquidity reserves (LTD FY23: 51%), with an increase in liquidity coverage ratios throughout the year. Furthermore, Portuguese banks significantly reduced their reliance on the Eurosystem funding by repaying portions of TLTRO III loans. Solvency remained strong, supported by a CET1 ratio of 17%, being above average in the Eurozone. Moreover, a higher leverage ratio of 6.8% reflects reduced debt reliance, further improving the resilience of Portuguese banks like BCTT to withstand economic uncertainties.

**Credit Risk and Profitability |** The Portuguese banking sector's non-performing loan ratio reduced to 2.7% in 2023, indicating improved asset quality. However, mortgage NPLs experienced a slight increase due to higher interest rates affecting variable-rate loans. BCTT, with its increasing exposure to mortgage loans, therefore has to remain careful in managing credit risk in this segment. The NPL coverage ratio of the Portuguese banking sector increased to 56.3%, above the Eurozone average, further strengthening the ability of Portuguese banks, to manage potential defaults. While higher net interest margins improved sector profitability, BCTT's ability to maintain profitability while mitigating credit risk will be central to its future strategy.

**Monetary Policy |** As of December 18th, 2024, the ECB lowered its key interest rates by 25bps to 3.0%, reinforcing its commitment to fostering economic growth. While rising interest rates previously supported robust net interest margins, the recent cuts introduce new challenges, with margins likely to face downward pressure as further reductions are anticipated throughout the year.

Figure 15: No. of Neobanking Users in PT in Mn

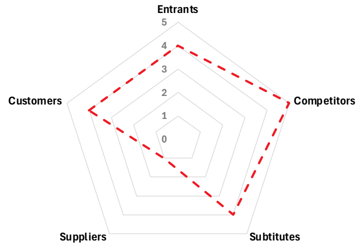



*Source: Statista Digital Market Insights*

**Digitalization |** The Financial Services industry is modernizing with the rise of Fintech and digitalized services, appealing to younger generations. Digital banking reached a level of 60% in 2023 in Portugal, driven by the growing interest from consumers for online banking. However, adoption has been comparatively slow in rural areas and among older populations, who make up 42% of Portugal's population. Nonetheless, CTT has responded to this trend by gradually expanding its digital services, offering mobile banking apps and digital financial solutions and plans to do so in the future as well.

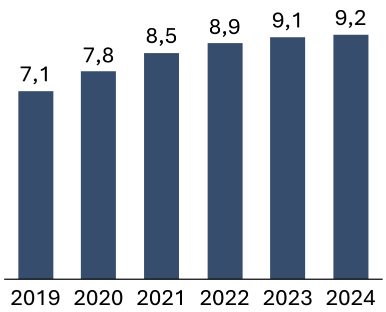
**Demand Drivers |** The demand for mortgage products is shaped by economic factors and several market conditions. For mortgage loans factors like, lower interest rates, economic growth, rising property values, and demographic trends such as urbanization and household formation are linked to growing demand. According to Banco de Portugal, disposable income increased by 7.1% in 2024 but this growth is expected to slow down and keep growing at a lower rate of around 1.9% in future years. This growth alongside a projected CAGR 25-29 of 0.3% in the passenger car markets in Portugal can be interpreted as positive indicators for car loans, hinting at possible growth in consumer spending and benefiting car loan providers.

Figure 16: Banco CTT Porter-Five-Forces



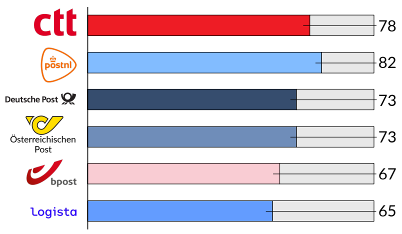

*Source: Team Estimates*

Figure 17: Number of Fintechs in Europe in k



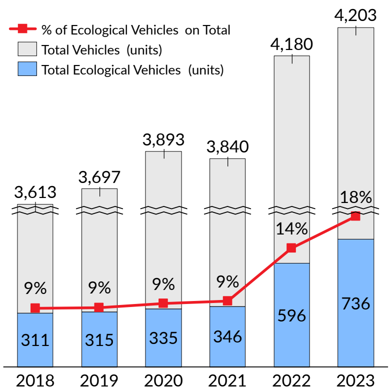

*Source: Statista Market Insight*

**Figure 18: ESG Score vs. Peers**




*Source: Refinitiv Eikon*

**Figure 19: Investments in Ecological Fleet CTT**




*Source: CTT Annual Reports*

Together, these factors are expected to increase demand for Banco CTT's loan offerings, contributing to growth in both segments.

**Supply Drivers |** A strong CET1 buffer and abundant, low-cost funding allow for an expansion of the mortgage portfolio. Any easing of regulatory caps or buyer subsidies would quickly release extra volume. Advanced credit analytics can compress underwriting times, effectively increasing the firm's mortgage production capacity. Auto loan growth is limited by risk-return hurdles and balance sheet liquidity. Stricter lending rules raise compliance costs, yet they also heighten entry barriers, favoring larger banks with greater scale. The ability to generate fee income depends on effectively managing the prices of deposits, payments, and cards. Digital add-ons that provide benefits like instant payments and BNPL help maintain pricing power. Additionally, a stable core deposit base can offset regulatory limits on interchange and overdraft charges.

**Competitive Positioning**

**Rivalry Among Existing Competitors** | High

The banking industry in Portugal is crowded and competitive, with new banks joining the market and established banks adjusting to the shifting demands of their customers. The majority of Portugal's deposits are held by four companies: CGD, Santander Totta, Millennium BCP, and Novo Banco. There is intense competition for all kinds of banking products. With 2,375 access points and 212 branches that offer access to less populated areas, BCTT's extensive postal network is its primary competitive advantage. Neo-banks and fintech, on the other hand, are joining the market with fast onboarding and cheap fees. BCTT needs to control its net interest margin and continue to offer competitive loan and savings rates if it hopes to sustain its 36% deposit growth.

**Threat of Substitute Products** | High

With competition from non-bank financial services, fintech platforms, alternative lending organizations, and other banks, BCTT's traditional banking services are at high risk of substitution. Digital wallets are taking the place of current accounts, peer-to-peer websites are undercutting consumer loans, investment apps are taking money out of deposits, and cryptocurrency platforms offer risk-seeking savers. Although younger clients were the first to use these tools, adoption rates are increasing for all age groups. Customers will look for alternatives if BCTT does not start to offer these digital features. Investments and ongoing service improvements are required to compete with these alternatives.

**Bargaining Power of Suppliers** | Low

The primary "suppliers" in the banking industry in the conventional sense are capital and technology providers, who offer crucial services and goods to the banking sector. Customer deposits, wholesale funding markets, and Eurosystem funding provide the capital, and technology suppliers supply the necessary infrastructure. Banco CTT's operations are financed by deposits from customers, and its cost of capital is impacted by market interest rates that are set by the European Central Bank. Because of the need for digital transformation, technology suppliers have a little more negotiating leverage. However, the risk of becoming overly dependent on any one supplier is reduced as there are several technology vendors available.

**Bargaining Power of Customers** | High

Due to low switching costs, greater transparency, and the emergence of digital alternatives, customers in the retail banking sector have especially strong bargaining power. Customers have many options when choosing a banking provider, whether they are looking for mortgages, savings accounts, or personal loans. When switching banks, they incur very little expense, particularly thanks to fintech platforms and mobile banking that make account transfers quick and simple. Higher customer expectations for individualized services, reduced fees, and instant transactions have also resulted from the banking industry's digital transformation. Banks like Banco CTT must constantly innovate and enhance customer experiences in order to keep customers loyal. Customers are extremely price-sensitive in a competitive market, particularly when interest rates are rising. As a result, they will actively look for greater savings returns and lower rates on loans.

**Threat of New Entrants** | Moderate to High

Fintech firms and digital disruptors have emerged in Portugal's banking sector, changing the competitive environment. Due to regulatory requirements and the requirement for considerable capital investment, traditional banks continue to face significant barriers to entry. However, by operating without extensive branch networks and providing efficient, tech-driven services, digital-only banks and fintech companies are reducing these barriers. These new firms are able to expand their operations rapidly, especially in urban areas where digital banking is widely used.

# ESG - Environment, Social and Governance

As noncompliance with standards can deter funding, companies with greater transparency and sustainable practices are increasingly attractive to investors. CTT is focusing on improving its operations and adopting sustainable practices. Refinitiv's ESG score of 78 reflects CTT's weighted average of the three pillars, and, as Figure 18 shows, CTT compares positively with most major postal operators in Europe.

**Table 6: CTT Stakeholder Structure**

| Shareholder | Shares | % Share Capital |
|---|---|---|
| Global Portfolio Investments, S.L. | 21,609,052 | 15.61% |
| Manuel Champalimaud, SGPS, S.A. | 19,747,000 | 14.26% |
| Green Frog Investments Inc | 13,500,000 | 9.75% |
| GreenWood Builders Fund I, LP | 9,777,400 | 7.06% |
| CTT, S.A. (own shares) | 3,461,309 | 2.50% |
| Other shareholders & Freefloat | 70,345,239 | 50.81% |
| Total | 138,440,000 | 100.00% |

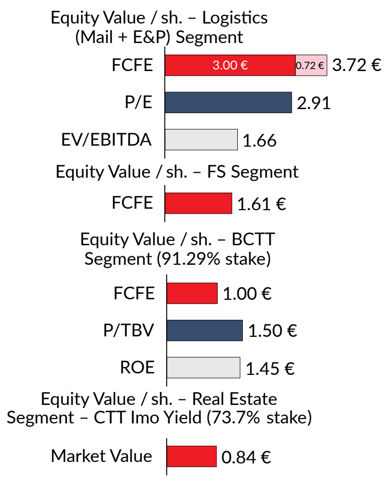
*Source: CTT Investor Relations*

**Table 7: CTT Equity Value**

| CTT Group Equity Value | Method | €k | €/sh. |
|---|---|---|---|
| **Equity Value by Segment** | | | |
| Logistics (Mail + Express & Parcels) | FCFE | 404,522 | 3.00 |
| FS | FCFE | 217,957 | 1.61 |
| Real Estate (73.7% stake) | Mkt Value | 113,086 | 0.84 |
| BCTT (91% stake) | FCFE | 134,788 | 1.00 |
| SoP Equity Value Base Case Scenario | | 870,354 | 6.45 |
| Contingent Liabilities | 9M24 BV x 75% | -8,421 | -0.06 |
| Pension Obligations not included in cash flows | Actuarial Value 9M24 | -178,922 | -1.33 |
| **SoP Equity Value Base Case Scenario (adjusted)** | | **683,011** | **5.06** |
| **Acquisition Impact** | | | |
| Increase in Value with Cacesa's Acquisition and DHL Joint Venture | Δ FCFE | 116,860 | 0.87 |
| Payment to Cacesa Net of Cash Proceeds from DHL JV | | -35,000 | -0.26 |
| DHL Parcel Iberia Stake (25%) | Transaction | 26,500 | 0.20 |
| Net Value from the acquisitions | | 108,360 | 0.80 |
| Probability of Approval from Regulators | Upon Approval | 90% | |
| Expected Net Value from the acquisitions | | 97,524 | 0.72 |
| **SoP Equity Value with Acquisitions** | **2025 YE** | **780,535** | **5.78** |
| Shares Outstanding | thousands | 134,979 | |
| Current Equity Value | As of Jan 9, 2025 | 724,836 | 5.37 |
| Upside / Downside | | 7.7% | |
| Cost of Equity | | 10% | |
| **Recommendation** | | **HOLD** | |

*Source: Team Estimates*

**Figure 20: Segments Value per Share by Method**




*Source: Team Estimates*

CTT categorizes its activities as either Eligible (Mail, Express & Parcels) or Non-Eligible (Banco CTT, Financial Services). In 2023, 72% of revenue came from taxonomy-eligible activities, with related CAPEX at 30% and OPEX at 49%.

**Environmental**

From 2022 to 2023, CTT reduced total $CO_2$ emissions by 2.6%. The company's goals are to reduce emissions by 30% by 2025 and by 20% per letter. In 2023, electric vehicles made up 19.6% of the fleet; management plans to reach 50% for last-mile vans by 2025 and full electrification by 2030. Although fuel still drives 64.8% of energy use, spending on new EVs nearly doubled year over year. Waste increased by 68.1% due to higher Asian parcel volume, but recovery reached 99.3%, surpassing the 75% target. Green capital expenditures climbed to €9 million in 2023, up 324% since 2018, and the firm retains ISO 14001 certification.

**Social**

In 2023, turnover stood at 18.7%, while new hires lifted the contracting rate to 37.5%. Though women held 37% of middle-management posts, senior management reached gender parity, and the pay gap ratio was 0.77. 90% of permanent staff completed training, and employee polls were conducted twice during the year. The number of road accidents per kilometer increased by 25.9%, missing the target of a 5% reduction, yet no fatal events occurred. The number of volunteering projects surpassed the goal with 15 projects and 1,832 hours, and strike activity continued to decline, supporting CTT's ranking as the top workplace in Portuguese transportation.

**Governance**

The free float is 51.6%, and Global Portfolio Investments is the largest shareholder. CTT owns 1.65% of its shares and plans to repurchase up to 8.5 million shares (€25M) by July 2025. In May 2024, ANACOM fined the company €400,000 for service issues, and CTT contested the decision in July. The 2023-25 board consists of three executives and eight non-executives, 36% of whom are women. The executive team, consisting of CEO João Bento, CFO Guy Pacheco, and CCO João Sousa, has extensive experience in the company and sector. 37.2% of director pay is variable and is split between annual and long-term share plans.

# Valuation

**Free Cash Flow to Equity (FCFE): a Sum of the Parts (SoP) Approach** | CTT's operations range across substantially different industries and hence the Group's cash flows are influenced by different value drivers, growth potentials, and risks. A SoP approach is deemed necessary to capture those factors and for being able to aggregate them into a target price. The presence of Banco CTT, which requires the use of an equity valuation approach, led to the implementation of this method along with all the business segments, aiming to harmonize the valuation process. The valuation considers forecasts for the period 2024E to 2029F. Appendix 6 expands on the valuation that we summarize below. The terminal value was defined through a required reinvestment rate, which allows connecting the reinvestment required to attain target growth and profitability levels.

**Revenue Forecast** | Banco CTT's forecast is based on loan income and expense. A ratio-based approach combined with macroeconomic indicators was used to project loan growth and yields. Mortgage credit is expected to decline to € 10.5M by FY29 due to easing EURIBOR rates. Motor vehicle credit will grow to € 71.9M by FY29 due to improving economic recovery. Other interest-earning assets are estimated conservatively. Total interest expense will rise to € 15.5M by FY29 due to deposit repricing and stable funding costs. Net interest income will be € 106.2M in FY29, with a 3.1% CAGR from 2024. Non-interest income from fees, commissions, and the Generali partnership will contribute to total net revenue of € 133.8M by FY29, with a 2.9% CAGR. This growth is supported by a strong capital position, with management anticipating a CET1 ratio increase of around 640 bps from 2024 to 2029.

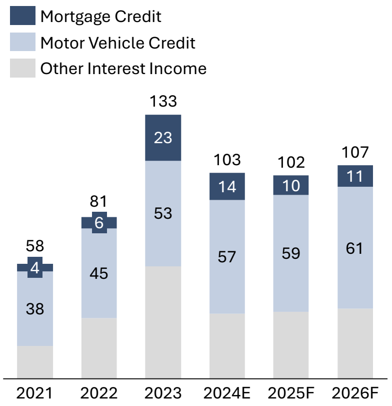
**Cost of Equity |** Different cost of equity figures for each business segment were set. The normalized 10-year German Government Bond Yield (2.20%) sets the riskless asset. Using the pure-play approach to compute the betas for each segment and considering the Portuguese Market Risk Premium (MRP) for Portugal 5.86% and Country Risk Premium 1.38% for almost all business segments.

**Terminal Period |** The terminal growth rate applied to each segment varies, reflecting their differing growth prospects. A 2% growth rate was applied to BCTT, aligned with the anticipated economic growth rate of Portugal.

**Alternative Methods - Precedent Transaction Analysis for BCTT |** The value precedent transactions valuation model was utilized to triangulate Banco's valuation through the FCFE approach, which employs industry multiples such as P/TBV and ROE. The benchmark multiples were sourced from M&A transactions in 2024 involving the target company's operations in the financial industry. The Equity Value of the Banking segment was calculated utilizing the computed P/TBV metric and taking into consideration the ROE.

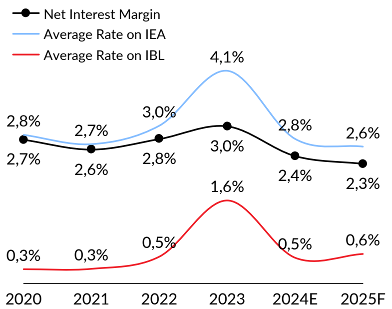
**Adjustments: Contingent Liabilities and Pension Liabilities |** Contingent liabilities result in an estimated €8.4M (-0.06 €/sh.). Pension liabilities do not have the corresponding assets, thus there is a full negative funded status. As the used SoP approach to cash flows and valuation disregards this responsibility, the FY24 actuarial value of €178M (-1.33 €/sh.) is adjusted in the valuation.

Figure 21: Interest Income in €M



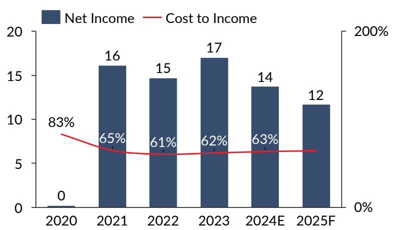

*Source: CTT Annual Reports, Team Estimates*

Figure 22: Average Interest Rate & NIM



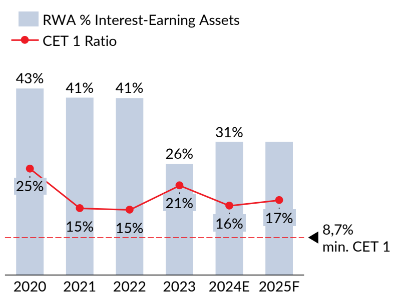

*Source: CTT Annual Reports, Team Estimates*

Figure 23: NI in €M and Cost-to-Income Ratio




*Source: CTT Annual Reports, Team Estimates*

Figure 24: RWA and CET1 Ratio




*Source: CTT Annual Reports, Team Estimates*

# Financial Analysis

**Profitability |** Due to an increase in mortgage and auto lending, BCTT turned a profit by 2020 after having negative earnings. Net interest income increased from € 10k 2016 to € 98.3M in 2023. By 2029, it is expected to reach € 106.2M. This expected growth a CAGR of 3.1% between 2024 and 2029, is due to interest rate normalization and loan growth. BCTT's early-stage growth and capital infusions are reflected in its historically volatile ROE. It is anticipated to level off at 4.1% by 2029, but will remain low due to earnings retention for strong capital ratios. The bank prioritizes preserving a solid capital base for stability and future projects over distributing retained earnings, even though doing so could increase ROE. Throughout the forecast period, ROA remains low at 0.4%, which is typical for retail banks. The yearly growth rate of non-interest income, including fees and commissions, is 3.7%. The Generali partnership, which provides consistent fixed payments, accounts for a significant portion of this revenue. While the fee and commission mix is still developing, it is to be expected that BCTT will leverage its extensive network and brand for cross-selling activities.

**Solvency |** Solvency remains the cornerstone of BCTT's strategy. As of 2023, it had € 196M in Tier 1 capital, giving it a Tier 1 ratio of 20.7%, which is considerably higher than the SREP requirement of 10.8%. However, in 2024, the ratio is expected to temporarily drop to 16.1% due to an increase in RWA due to loan growth. The ratio is then projected to gradually increase to approximately 22.5% by 2029, reflecting a CAGR of 1.3% from 2023 to 2029. CET1 and total capital ratios remained well above the regulatory minimums of 8.7% and 13.5%, respectively, reaching 20.7% in 2023. Given CTT's intention to sell more shares of the bank, it is reasonable to assume that management will prioritize maintaining healthy capital reserves over leveraging or allocating retained earnings. This cautious strategy demonstrates the bank's sound financial standing and steady, long-term growth, attracting potential buyers and boosting investor confidence.

**Liquidity |** BCTT's robust deposit business has seen funds grow to € 3.1 bn by 2023, with an expected increase to € 4.2 bn by 2029. This growth has outpaced loan expansion, resulting in a Net Loan-to-Deposit Ratio of 51.3% in 2023, compared to an estimated 75.3% average in Portugal (Sep. 2024). BCTT's moderate reliance on debt securities supports its liquidity profile. This enables it to comfortably meet short-term obligations and manage funding volatility without compromising growth prospects.

**Efficiency |** BCTT's Cost-to-Income Ratio, which was initially high due to the company's relatively recent establishment, declined to around 62% by 2023 thanks to increased revenue. However, future investments in IT platform development and employee training will keep the ratio at approximately 60% through 2029, as these investments are expected to be costly. Although this figure remains above the Portuguese average of 38.3%, these strategic investments are crucial for CTT's long-term digital competitiveness and enhanced cross-selling capabilities.

**Asset Quality |** BCTT's lower-risk mortgage and auto lending are the source of the historically high asset quality. Subdued non-performing loan ratios, however, are anticipated to marginally rise as the bank diversifies into higher-risk areas and interest rates rise. After rising from 0.1% in 2022 to 1.8% in 2023, the net charge-off ratio is predicted to level off at 0.7%. As a result of the bank's cautious approach to provisioning in a more unpredictable credit environment, the reserve ratio (Allowance for loan losses/ Gross loans) is anticipated to increase from 2.9% in 2023 to 6.4% by 2029. Overall, management's cautious underwriting and significant reserve accumulation should lessen any potential negative effects, even though asset quality metrics may slightly worsen.

**Growth |** BCTT's loan portfolio increased from €79M to €1.6 bn between 2017 and 2023, and it is expected to grow at a CAGR of 3.8% to reach €2.2 bn by 2029 and deposits are expected to surpass €4.2 bn. By 2029, total net revenue will have surpassed €130M, although growth will slow as the bank moves out of its ramp-up phase. BCTT is well-positioned to gain market share in Portugal's retail banking sector thanks to its well-known brand and synergies with the CTT infrastructure. Appendix 3 provides a detailed explanation of the growth assumptions.

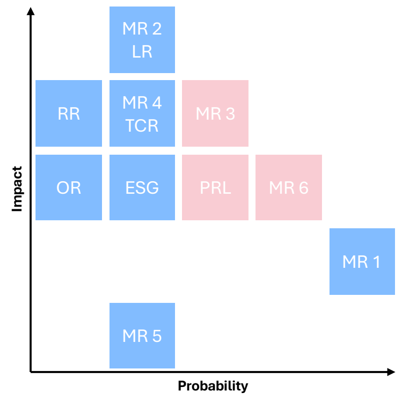
**Summary |** BCTT is transitioning from quick growth to steady expansion. Increasing NII and fee income boosts profitability, but conservative capital retention restricts ROE numbers. With an emphasis on keeping sizable capital reserves, especially in view of CTT's possible future strategic directions, solvency exceeds regulatory requirements. All things considered, a solid foundation for development is provided by strong capital, asset quality, and revenue growth. But there are still issues to deal with, like keeping competitive metrics and managing risk in the loan portfolio. Deliberate expansion and strategic capital management will put the bank in a position to handle Portugal's changing financial environment and draw in possible future investors.

# Investment Risks

**MR 1 | Market Risk | Interest Rate**

BCTT's profitability is subject to fluctuations in interest rates, which, due to the bank's exposure to variable rates, directly impacts net interest margins. An increase in interest rates can lead to an increase in borrowing costs, which results in a decrease in loan demand. This increase has the potential to drive up the cost of deposits as well. Although BCTT employs fixed rates in its auto loan segment to partially

Figure 25: Risk Matrix




*Source: Team Estimates*

mitigate this risk, the mortgage loan portfolio mostly consists of variable-rate contracts, leaving the bank exposed to potential margin compression during periods of rising interest rates.

**MR 2 | Market Risk | Macroeconomic Factors**

Macroeconomic variables such as economic downturns, inflation, and political instability in Portugal and other regions are potential factors that can negatively impact the performance of BCTT. The bank closely monitors macroeconomic conditions and limits its exposure to market risks by managing its own portfolio against predefined risk tolerance levels. These measures are subject to review by the Board of Directors and its associated committees, with the aim of ensuring their alignment with the strategic objectives of the organization.

**MR 3 | Market Risk | Competition**

BCTT faces competitive pressure from traditional banks and digital-only entrants, particularly in urban markets where fintech firms are rapidly expanding. The bank leverages its USP of physical locations, in rural areas as well as urban ones, to differentiate its services. To address further competitive dynamics, BCTT plans to enhance the training of its banking staff and accelerate investments in its digital banking platform to remain competitive.

**MR 4 | Market Risk | Credit Risk**

BCTT is exposed to credit risk due to its loan portfolio. To mitigate this risk, the bank employs a credit risk assessment methodology that evaluates customers' repayment capacity and establishes credit limits. Additionally, sector diversification, particularly focusing on mortgage and auto loans, is employed to reduce risk. Furthermore, securitization strategies for auto loans are utilized to transfer potential risks.

**MR 5 | Market Risk | Urbanization**

CTT has a strong presence in rural areas, but 68.6% of the Portuguese population live in urban areas, and this number is expected to rise to 75% by 2040. This urbanization trend could potentially lead to a decrease in demand for traditional financial services in physical locations like money orders and payments, which are more commonly performed in rural regions. To address this, CTT is exploring ways to modernize its services and align them with urbanization trends. These include mainly enhancing its digital service offerings.

**MR 6 | Market Risk | Demographic Change**

In Portugal, 41.8% of the population is currently over 55 and this percentage is expected to increase to almost 50% by 2040. Even considering the rapid rate at which the population is aging, younger generations might no longer rely on the same services and investments as the previous ones did. The generational change is already affecting heavily the Mail business. Moreover, Financial Services might also be affected by this evolution in the long run due to changes in investor profiles, leading to alternative investment choices. CTT can leverage cross-selling over all the businesses of the group to soften the trend.

**OR | Operational Risk**

Operational risks emerge from inadequate or unsuccessful internal processes, systems, human actions, or external events. These risks have the potential to cause significant disruption to daily operations. Common examples include system outages, inefficiencies in processes, or errors in service delivery, all of which have the potential to impact BCTT negatively. These risks are addressed through a comprehensive framework integrating risk identification, assessment, and mitigation across all functional units, ensuring compliance with the Internal Control System.

**RR | Reputational Risk**

In the context of CTT's operating sectors, reputation holds significant weight in fostering trust. However, this trust is subject to potential threats, including compliance breaches, operational failures, and negative publicity. Such events have the potential to disrupt confidence, resulting in a loss of customers and the possibility of liquidity pressures. To mitigate this risk, CTT reinforces its Code of Conduct through regular training. A total of 4,200 employees participated in anti-corruption training, and 903 employees received targeted instruction on anti-money laundering and counter-terrorism financing. These measures are designed to enhance ethical awareness and protect CTT's reputation from internal threats.

**TCR | Technology & Cybersecurity Risk**

As the use of digital services continues to expand, CTT faces heightened exposure to cybersecurity threats, including data breaches and operational disruptions. To address these concerns, CTT has implemented a range of security controls, policies, and governance structures. It conducts employee training on best practices for telework and raises awareness about relevant topics. Furthermore, the Information Security Forum conducts continuous monitoring of risk exposure and oversees strategic and tactical initiatives to strengthen the overall position in mitigating cybersecurity risks.

**LR | Liquidity Risk**

Liquidity risk for CTT involves the potential for substantial losses resulting from a decline in financing conditions and the involuntary sale of assets. The company has implemented a comprehensive risk management strategy to mitigate potential financial losses. This strategy involves the establishment of liquidity risk limits, adherence to regulatory standards, and the implementation of monitoring processes. The monitoring processes involve the observation of key risk indicators on a quarterly basis. Nevertheless, external shocks and unforeseen market conditions could still pose challenges to CTT's capacity to maintain sufficient liquidity.

**PRL | Political, Regulatory and Legal Risk | Compliance and Legal**

Operating within a regulated environment, Banco CTT is required to ensure compliance with anti-money laundering and data protection regulations, including GDPR. Failure to comply with these regulations would result in severe penalties and reputational damage. In order to address these potential risks, the bank has implemented an integrated risk management system and a governance model that adheres to the "three lines of defense" framework. This system entails active involvement from the top management level to the operational level, with the establishment of internal controls and adherence to regulatory requirements.

# Appendix C: Appendices of CTT Group Equity Research

## Appendix 1 - Consolidated Financial Statements:

| Consolidated Income Statement (€k) | 2019 | 2020 | 2021 | 2022 | 2023 | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F | CAGR 25-29 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Revenues** | **740,286** | **745,240** | **847,870** | **906,625** | **985,219** | **1,011,804** | **1,161,785** | **1,279,883** | **1,349,788** | **1,425,355** | **1,479,846** | **6.2%** |
| Sales and services rendered | 688,022 | 672,854 | 757,727 | 788,582 | 844,606 | 895,654 | 1,046,646 | 1,159,417 | 1,223,123 | 1,292,001 | 1,346,004 | 6.5% |
| Financial margin | 29,316 | 44,637 | 55,776 | 74,357 | 98,791 | 91,258 | 89,432 | 93,859 | 99,082 | 104,815 | 106,196 | 4.4% |
| Other operating income | 22,948 | 27,749 | 34,367 | 43,686 | 41,821 | 24,893 | 25,707 | 26,608 | 27,583 | 28,539 | 27,646 | 1.8% |
| Operating costs | (693,001) | (710,733) | (785,998) | (850,498) | (907,441) | (934,554) | (1,067,766) | (1,186,102) | (1,242,729) | (1,314,963) | (1,371,037) | 6.4% |
| External supplies and services | (242,777) | (256,145) | (330,551) | (343,216) | (394,021) | (412,518) | (509,004) | (602,882) | (639,007) | (689,249) | (727,936) | 9.4% |
| Staff costs | (356,004) | (342,488) | (358,013) | (358,237) | (365,020) | (395,403) | (419,249) | (440,116) | (454,454) | (469,950) | (483,885) | 3.6% |
| Other Operating Costs | (77,987) | (49,964) | (39,428) | (80,632) | (82,665) | (61,235) | (65,564) | (64,652) | (66,761) | (68,963) | (69,325) | 1.4% |
| **EBITDA** | **63,518** | **96,643** | **119,878** | **124,540** | **143,513** | **142,649** | **167,969** | **172,233** | **189,565** | **197,194** | **198,701** | **4.3%** |
| Depreciation/amortization and impairment of investments, net | (16,233) | (62,136) | (58,006) | (68,413) | (65,735) | (65,399) | (73,950) | (78,452) | (82,507) | (86,802) | (89,891) | 5.0% |
| **EBIT** | **47,285** | **34,507** | **61,872** | **56,127** | **77,778** | **77,250** | **94,020** | **93,781** | **107,059** | **110,392** | **108,809** | **3.7%** |
| Financial results | (11,758) | (11,382) | (11,064) | (9,413) | (16,240) | (12,638) | (13,951) | (14,996) | (15,740) | (16,809) | (17,685) | 6.1% |
| **EBT** | **35,527** | **(9,660)** | **(8,532)** | **(9,256)** | **(16,870)** | **(12,638)** | **(13,951)** | **(14,996)** | **(15,740)** | **(16,809)** | **(17,685)** | **6.1%** |
| Income tax for the period | (6,242) | (6,359) | (12,216) | (10,372) | (1,096) | (14,497) | (17,916) | (17,622) | (20,451) | (20,980) | (20,439) | 3.3% |
| **Net profit for the period** | **29,285** | **16,767** | **38,591** | **36,342** | **60,442** | **50,114** | **62,153** | **61,162** | **70,868** | **72,603** | **70,686** | **3.3%** |
| Equity holders | 29,197 | 16,669 | 38,404 | 36,407 | 60,511 | 49,461 | 54,913 | 52,762 | 61,125 | 61,411 | 58,434 | |
| Non-controlling interests | 88 | 97 | 187 | (64) | (69) | 653 | 7,240 | 8,401 | 9,743 | 11,191 | 12,252 | |
| Earnings per share: | 0.19 | 0.11 | 0.26 | 0.25 | 0.43 | 0.37 | 0.41 | 0.39 | 0.45 | 0.45 | 0.43 | |

| Consolidated Balance Sheet (€k) | 2019 | 2020 | 2021 | 2022 | 2023 | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F | Notes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Tangible fixed assets | 263,443 | 294,989 | 296,288 | 303,206 | 296,995 | 331,712 | 323,332 | 302,747 | 291,636 | 284,693 | 275,770 | see Asset Schedule |
| Investment properties | 7,653 | 7,076 | 6,327 | 6,184 | 5,976 | 6,051 | 6,051 | 6,051 | 6,051 | 6,051 | 6,051 | |
| Intangible assets | 62,013 | 58,017 | 63,507 | 69,409 | 70,640 | 71,347 | 70,599 | 68,788 | 65,553 | 60,894 | 54,811 | see Asset Schedule |
| Goodwill | 70,202 | 70,202 | 81,471 | 80,257 | 80,257 | 80,257 | 164,602 | 164,602 | 164,602 | 164,602 | 164,602 | |
| Investments in joint ventures | 2,724 | 2,925 | 18 | - | 22 | 22 | 22 | 22 | 22 | 22 | 22 | |
| Financial assets at fair value through profit or loss | - | 2 | 2,262 | 26,220 | 13,532 | 14,094 | 14,794 | 15,560 | 16,522 | 17,347 | 18,230 | |
| Debt securities at amortized cost | - | 453,091 | 294,987 | 409,389 | 364,706 | 382,024 | 400,997 | 421,767 | 447,848 | 470,202 | 494,133 | see BCTT details |
| Other non-current assets | 536,161 | 112,657 | 99,484 | 70,925 | 78,130 | 78,130 | 80,121 | 80,121 | 80,121 | 80,121 | 80,121 | |
| Credit to banking clients | 792,470 | 985,356 | 1,125,984 | 1,287,676 | 1,444,412 | 1,492,786 | 1,556,575 | 1,626,993 | 1,718,230 | 1,793,461 | 1,874,316 | see BCTT details |
| Total non-current assets | 1,734,665 | 1,984,314 | 1,970,328 | 2,253,265 | 2,354,670 | 2,456,424 | 2,617,093 | 2,686,651 | 2,790,586 | 2,877,394 | 2,968,056 | |
| Inventories | 5,860 | 6,602 | 6,872 | 8,041 | 6,663 | 11,172 | 13,655 | 16,064 | 17,015 | 18,325 | 19,328 | see NWC Schedule |
| Accounts receivable | 146,472 | 153,616 | 160,930 | 147,131 | 153,062 | 163,425 | 171,704 | 178,160 | 186,270 | 194,561 | 199,604 | |
| Credit to banking clients | 93,351 | 107,926 | 415,924 | 489,889 | 148,802 | 164,330 | 171,352 | 179,103 | 189,147 | 197,429 | 206,330 | |
| Debt securities at amortized cost | - | 45,160 | 39,174 | 128,392 | 364,760 | 1,561,793 | 1,830,805 | 1,902,834 | 1,982,285 | 2,027,686 | 2,152,108 | |
| Other current assets | 75,437 | 49,648 | 104,376 | 113,076 | 102,501 | 102,493 | 102,493 | 102,493 | 102,493 | 102,493 | 102,493 | |
| Other banking financial assets | 14,660 | 29,457 | 9,722 | 461,226 | 1,274,575 | 769,285 | 601,008 | 665,989 | 776,218 | 879,779 | 890,916 | see BCTT details |
| Cash and cash equivalents | 442,996 | 518,180 | 877,873 | 456,469 | 351,610 | 383,730 | 444,916 | 530,205 | 560,828 | 607,570 | 644,908 | |
| from CF (excl. BCTT) | | | | | | 305,123 | 364,548 | 447,910 | 476,112 | 520,780 | 555,897 | |
| from BCTT BS | | | | | | 78,607 | 80,368 | 82,295 | 84,716 | 86,790 | 89,011 | |
| Total current assets | 778,776 | 910,588 | 1,614,870 | 1,804,224 | 2,401,972 | 3,156,227 | 3,335,933 | 3,574,848 | 3,814,255 | 4,027,842 | 4,215,688 | |
| **Total assets** | **2,513,441** | **2,894,903** | **3,585,199** | **4,057,488** | **4,756,642** | **5,612,651** | **5,953,025** | **6,261,499** | **6,604,841** | **6,905,236** | **7,183,744** | |
| Share capital | 75,000 | 75,000 | 75,000 | 72,675 | 71,958 | 69,220 | 69,220 | 69,220 | 69,220 | 69,220 | 69,220 | |
| Own shares | (0) | (0) | (6,405) | (10,826) | (15,625) | (8,948) | (8,948) | (8,948) | (8,948) | (8,948) | (8,948) | |
| Reserves | 65,853 | 65,920 | 67,078 | 53,844 | 48,113 | 30,510 | 30,510 | 30,510 | 30,510 | 30,510 | 30,510 | |
| Retained earnings | 10,867 | 39,962 | 43,904 | 64,647 | 83,269 | 119,951 | 147,154 | 178,455 | 208,529 | 246,102 | 283,850 | |
| Other changes in equity | (49,744) | (47,600) | (43,999) | 6,857 | 3,402 | 3,409 | 3,409 | 3,409 | 3,409 | 3,409 | 3,409 | see Equity appedinx |
| Net profit | 29,197 | 16,669 | 38,404 | 36,407 | 60,511 | 50,114 | 62,153 | 61,162 | 70,868 | 72,603 | 58,434 | |
| Equity attributable to equity holders of the Parent Company | 131,173 | 149,951 | 173,983 | 223,603 | 251,629 | 264,257 | 303,499 | 333,809 | 373,589 | 412,896 | 436,476 | |
| Non-controlling interests | 242 | 324 | 563 | 1,326 | 1,624 | 33,564 | 34,217 | 41,458 | 49,858 | 59,601 | 70,793 | |
| **Total equity** | **131,415** | **150,275** | **174,546** | **224,929** | **253,253** | **297,821** | **337,716** | **375,266** | **423,447** | **472,497** | **507,269** | |
| Medium and long term debt | 148,598 | 164,034 | 149,336 | 136,198 | 161,080 | 196,141 | 230,956 | 236,818 | 260,650 | 271,139 | 273,211 | see Debt Schedule |
| Employee benefits | 267,287 | 264,369 | 260,806 | 185,258 | 149,740 | 149,740 | 149,740 | 149,740 | 149,740 | 149,740 | 149,740 | |
| Provisions | 17,635 | 17,416 | 14,680 | 12,632 | 26,339 | 26,339 | 26,339 | 26,339 | 26,339 | 26,339 | 26,339 | |
| Debt securities issued at amortised cost | 76,060 | 44,507 | 277,761 | 445,226 | 347,132 | 361,539 | 379,494 | 399,150 | 423,833 | 444,988 | 467,636 | see BCTT details |
| Other non-current liabilities | 3,253 | 3,077 | 2,700 | 10,108 | 5,342 | 5,342 | 5,342 | 5,342 | 5,342 | 5,342 | 5,342 | |
| Total non-current liabilities | 512,833 | 493,404 | 705,282 | 789,422 | 689,633 | 739,101 | 791,872 | 817,390 | 865,905 | 897,549 | 922,268 | |
| Accounts payable | 373,791 | 375,563 | 350,304 | 525,212 | 373,961 | 385,769 | 457,365 | 521,912 | 536,239 | 560,205 | 573,143 | see NWC Schedule |
| Banking clients' deposits and other loans | 1,321,418 | 1,688,465 | 2,121,511 | 2,245,330 | 3,090,963 | 3,844,039 | 4,005,619 | 4,182,499 | 4,404,619 | 4,594,991 | 4,798,791 | see BCTT details |
| Employee benefits | 19,416 | 18,631 | 21,090 | 22,092 | 22,049 | 24,120 | 25,574 | 26,847 | 27,722 | 28,667 | 29,517 | |
| Short term debt | 26,814 | 42,833 | 51,783 | 59,757 | 107,935 | 70,613 | 83,147 | 85,258 | 93,837 | 97,613 | 98,359 | see Debt Schedule |
| Financial liabilities at fair value through profit or loss | - | - | - | 26,345 | 13,744 | 10,680 | 11,210 | 11,791 | 12,520 | 13,145 | 13,814 | |
| Debt securities issued at amortised cost | - | - | 35 | 352 | 243 | 254 | 266 | 280 | 297 | 312 | 328 | |
| Other current liabilities | 109,767 | 104,246 | 133,659 | 117,839 | 157,101 | 157,101 | 157,101 | 157,101 | 157,101 | 157,101 | 157,101 | |
| Other banking financial liabilities | 17,988 | 21,487 | 26,988 | 46,211 | 47,760 | 83,155 | 83,155 | 83,155 | 83,155 | 83,155 | 83,155 | |
| Total current liabilities | 1,869,193 | 2,251,224 | 2,705,371 | 3,043,136 | 3,813,756 | 4,575,730 | 4,823,437 | 5,068,842 | 5,315,490 | 5,535,189 | 5,754,208 | |
| **Total liabilities** | **2,382,026** | **2,744,628** | **3,410,653** | **3,832,559** | **4,503,389** | **5,314,830** | **5,615,309** | **5,886,232** | **6,181,394** | **6,432,738** | **6,676,476** | |
| **Total equity and liabilities** | **2,513,441** | **2,894,903** | **3,585,199** | **4,057,488** | **4,756,642** | **5,612,651** | **5,953,025** | **6,261,499** | **6,604,841** | **6,905,236** | **7,183,744** | |

| Consolidated Cash Flow Statement (excl. BCTT) (€k) | 2019 | 2020 | 2021 | 2022 | 2023 | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F | Notes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Collections from customers | 664,481 | 663,468 | 740,512 | 822,216 | 861,167 | 895,654 | 1,046,646 | 1,159,417 | 1,223,123 | 1,292,001 | 1,346,004 | |
| Payments to suppliers | (285,307) | (309,560) | (383,513) | (442,640) | (432,066) | (412,518) | (509,004) | (602,882) | (639,007) | (689,249) | (727,936) | |
| Payments to employees | (327,851) | (317,791) | (325,607) | (333,526) | (361,412) | (395,403) | (419,249) | (440,116) | (454,454) | (469,950) | (483,885) | |
| Other changes (BCTT) | 166,469 | 197,048 | (15,063) | (119,174) | 1,037,181 | - | - | - | - | - | - | |
| Cash flow generated by operations | 217,791 | 233,165 | 16,329 | (73,125) | 1,104,871 | 87,733 | 118,394 | 116,418 | 129,662 | 132,802 | 134,183 | |
| Payments/receivables of income taxes | 2,229 | (8,969) | (3,621) | (16,360) | (1,583) | (14,497) | (17,916) | (17,622) | (20,451) | (20,980) | (20,439) | |
| Other receivables/payments | 86,121 | 58,791 | 40,600 | 249,494 | (96,516) | 1,445 | 63,316 | 58,092 | 6,217 | 15,676 | 7,894 | |
| **Cash flow from operating activities** | **306,142** | **282,986** | **53,308** | **160,009** | **1,006,772** | **74,680** | **163,793** | **156,888** | **115,427** | **127,498** | **121,639** | |
| Tangible fixed assets | (18,752) | (25,398) | (16,778) | (16,059) | (14,833) | (16,909) | (17,018) | (18,121) | (20,171) | (17,148) | (16,763) | |
| Intangible assets | (17,514) | (12,431) | (14,343) | (17,822) | (16,008) | (17,941) | (17,941) | (17,941) | (17,941) | (17,941) | (17,941) | |
| Acquisition of Business | - | - | - | - | - | - | - | - | - | - | - | |
| Other changes (BCTT) | (59,951) | (61,695) | 162,861 | (653,505) | (983,926) | - | - | - | - | - | - | |
| **Cash flow from investing activities** | **(96,218)** | **(99,523)** | **131,740** | **(687,386)** | **(1,014,767)** | **(34,850)** | **(34,959)** | **(36,062)** | **(38,112)** | **(35,089)** | **(34,704)** | |
| Net Loans | 29,548 | (113) | (10,516) | (15,761) | 77,793 | (5,276) | 33,989 | 34,067 | 22,752 | 26,004 | 22,180 | |
| Interest expenses | (879) | (1,443) | (284) | (433) | (2,558) | (12,638) | (13,951) | (14,996) | (15,740) | (16,809) | (17,685) | see Debt Schedule |
| Finance leases | (26,991) | (28,529) | (30,343) | (33,708) | (37,046) | (31,323) | (32,190) | (32,922) | (33,438) | (33,384) | (32,651) | |
| Acquisition of own shares | - | - | (6,405) | (21,574) | (10,154) | (13,763) | - | - | - | - | - | see Equity Appendix |
| Dividends | (15,000) | - | (12,750) | (17,656) | (17,888) | (23,316) | (22,257) | (23,612) | (22,688) | (23,552) | (23,663) | |
| Other changes (BCTT) | (203,407) | (69,417) | 228,465 | 170,352 | (97,723) | - | - | - | - | - | - | |
| **Cash flow from financing activities** | **(216,729)** | **(99,502)** | **168,167** | **81,218** | **(87,575)** | **(86,316)** | **(34,409)** | **(37,464)** | **(49,113)** | **(47,741)** | **(51,818)** | |
| Net Change in Cash (1+2+3) | (6,805) | 83,961 | 353,215 | (446,159) | (95,570) | (46,487) | 59,425 | 83,362 | 28,202 | 44,668 | 35,117 | |
| Other changes | 6,824 | - | 4,916 | - | - | - | - | - | - | - | - | |
| Cash at the beginning of the period | 414,847 | 414,866 | 498,827 | 856,958 | 410,799 | 351,610 | 305,123 | 364,548 | 447,910 | 476,112 | 520,780 | |
| Cash at the end of the period | 414,866 | 498,827 | 856,958 | 410,799 | 315,229 | 305,123 | 364,548 | 447,910 | 476,112 | 520,780 | 555,897 | |
| Other changes (BCTT) | 28,130 | 19,353 | 20,915 | 45,670 | 36,380 | - | - | - | - | - | - | |
| **Cash and Cash Equivalent** | **442,996** | **518,180** | **877,873** | **456,469** | **351,610** | **305,123** | **364,548** | **447,910** | **476,112** | **520,780** | **555,897** | |
| (+) Cash from BCTT BS | | | | | | 78,607 | 80,368 | 82,295 | 84,716 | 86,790 | 89,011 | |
| **Cash and Cash Equivalent (BS)** | **-** | **-** | **-** | **-** | **-** | **383,730** | **444,916** | **530,205** | **560,828** | **607,570** | **644,908** | |

# Appendix 2 - Notes to the Consolidated Financial Statements:

| Asset Schedule | 2019 | 2020 | 2021 | 2022 | 2023 | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Tangible Fixed assets (beg. of the year) | 264,709 | 263,443 | 294,989 | 296,288 | 303,206 | 296,995 | 331,712 | 323,332 | 302,747 | 291,636 | 284,693 |
| CAPEX (Tangible) | 27,083 | 19,468 | 17,468 | 16,696 | 17,696 | 16,909 | 17,018 | 18,121 | 20,171 | 17,148 | 16,763 |
| New Contracts (RoU) | 6,995 | 28,653 | 28,610 | 32,163 | 13,627 | 61,412 | 27,982 | 19,578 | 29,578 | 39,578 | 39,578 |
| Depreciation | 40,922 | 44,219 | 44,843 | 48,608 | 52,157 | 48,165 | 55,260 | 58,700 | 61,330 | 64,202 | 65,867 |
| Terminated contracts (RoU) | 47,988 | 4,766 | - | - | 1,668 | 194 | - | - | 6,995 | 28,653 | 28,610 |
| **Tangible Fixed assets YE** | **263,443** | **294,989** | **296,288** | **303,206** | **296,995** | **331,712** | **323,332** | **302,747** | **291,636** | **284,693** | **275,770** |
| Intangible Fixed assets (beg. of the year) | 56,771 | 62,013 | 58,017 | 63,507 | 69,409 | 70,640 | 71,347 | 70,599 | 68,788 | 65,553 | 60,894 |
| CAPEX (Intangible) | 18,359 | 13,970 | 18,679 | 20,298 | 18,400 | 17,941 | 17,941 | 17,941 | 17,941 | 17,941 | 17,941 |
| Amortization | 13,538 | 17,887 | 13,063 | 16,266 | 17,034 | 17,234 | 18,689 | 19,752 | 21,176 | 22,600 | 24,024 |
| **Intangible Fixed assets YE** | **62,013** | **58,017** | **63,507** | **69,409** | **70,640** | **71,347** | **70,599** | **68,788** | **65,553** | **60,894** | **54,811** |

| NWC Schedule | 2019 | 2020 | 2021 | 2022 | 2023 | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Inventories | 5,860 | 6,602 | 6,872 | 8,041 | 6,663 | 11,172 | 13,655 | 16,064 | 17,015 | 18,325 | 19,328 |
| Days | 12 | 13 | 10 | 10 | 8 | 12 | 12 | 12 | 12 | 12 | 12 |
| Accounts receivable | 146,472 | 153,616 | 160,930 | 147,131 | 153,062 | 163,425 | 171,704 | 178,160 | 186,270 | 194,561 | 199,604 |
| Days | 72 | 75 | 69 | 59 | 57 | 57 | 57 | 57 | 57 | 57 | 57 |
| Accounts payable | 373,791 | 375,563 | 350,304 | 525,212 | 373,961 | 385,769 | 457,365 | 521,912 | 536,239 | 560,205 | 573,143 |
| Days | 790 | 714 | 496 | 658 | 442 | 428 | 416 | 403 | 391 | 379 | 368 |

| Debt Schedule | 2019 | 2020 | 2021 | 2022 | 2023 | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Total Debt | 175,412 | 206,867 | 201,119 | 195,955 | 269,015 | 248,518 | 274,686 | 288,476 | 299,769 | 322,790 | 340,747 |
| ST | 26,814 | 42,833 | 51,783 | 59,757 | 107,935 | 70,613 | 83,147 | 85,258 | 93,837 | 97,613 | 98,359 |
| % ot Total Debt | 15% | 21% | 26% | 30% | 40% | 28% | 30% | 30% | 31% | 30% | 29% |
| Medium and LT | 148,598 | 164,034 | 149,336 | 136,198 | 161,080 | 196,141 | 230,956 | 236,818 | 260,650 | 271,139 | 273,211 |
| % ot Total Debt | 85% | 79% | 74% | 70% | 60% | 79% | 84% | 82% | 87% | 84% | 80% |
| Total Debt to EBITDA | 2.76 | 2.14 | 1.68 | 1.57 | 1.87 | 1.87 | 1.87 | 1.87 | 1.87 | 1.87 | 1.87 |
| of which Lease Liabilities | 78,049 | 113,240 | 114,258 | 126,353 | 121,607 | 162,991 | 155,171 | 134,894 | 123,434 | 120,451 | 116,228 |
| Repayments | | | | | | (82,418) | (17,105) | (21,513) | (24,880) | (25,710) | (44,514) |
| Borrowings | | | | | | 17,189 | 51,094 | 55,580 | 47,633 | 51,713 | 66,695 |
| Net Borrowing | | | | | | (65,229) | 33,989 | 34,067 | 22,752 | 26,004 | 22,180 |

| Equity | 2019 | 2020 | 2021 | 2022 | 2023 | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Retained Earnings (beg. of the Year) | 4,379 | 10,867 | 39,962 | 43,904 | 64,647 | 83,269 | 119,951 | 147,154 | 178,455 | 208,529 | 246,102 |
| (+) Net Profit (previous Year) | 21,499 | 29,197 | 16,669 | 38,404 | 36,407 | 60,511 | 49,461 | 54,913 | 52,762 | 61,125 | 61,411 |
| (-) Dividends | (15,000) | - | (12,750) | (17,656) | (17,888) | (23,316) | (22,257) | (23,612) | (22,688) | (23,552) | (23,663) |
| Payout Ratio | 70% | 0% | 76% | 46% | 49% | 39% | 45% | 43% | 43% | 39% | 39% |
| Retained Earnings YE | 10,867 | 39,962 | 43,904 | 64,647 | 83,269 | 119,951 | 147,154 | 178,455 | 208,529 | 246,102 | 283,850 |

# Appendix 3 - Income Statement Assumptions and Drivers:

| Banco Income Statement | Unit | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F | Notes for Assumptions | CAGR 24-29 |
|---|---|---|---|---|---|---|---|---|---|
| **Indicators** | | | | | | | | | |
| EURIBOR 12m | % | 2.5% | 1.9% | 1.9% | 1.9% | 1.9% | 1.5% | Economist Intelligence Unit Estimate/ Forecast | (9.7%) |
| Credit Growth PT | % | 1.8% | 3.7% | 5.2% | 6.2% | 5.0% | 5.1% | Economist Intelligence Unit Estimate/ Forecast | 23.2% |
| Fin. & Insurance Growth PT | % | (0.5%) | 2.5% | 2.6% | 2.7% | 2.9% | 1.8% | Economist Intelligence Unit Estimate/ Forecast | 31.3% |
| **Breakdown** | | | | | | | | | |
| Total Net Revenue | €M | 116.2 | 115.1 | 120.5 | 126.7 | 133.4 | 133.8 | Revenue growth is modest, reflecting loan growth, a stabilizing interest rate environment and a gradual increase in fee-based activities. | 2.9% |
| Net Interest Income | €M | 91.3 | 89.4 | 93.9 | 99.1 | 104.8 | 106.2 | | 3.1% |
| Total Interest Income | €M | 103.3 | 102.0 | 107.1 | 113.1 | 119.6 | 121.7 | | 3.3% |
| Interest Income on Loans | €M | 71.2 | 68.8 | 72.4 | 77.0 | 81.8 | 82.8 | | 3.1% |
| Mortgage Credit | €M | 13.6 | 9.7 | 10.7 | 11.7 | 12.9 | 10.5 | Mortgage loan growth is expected to slow over the forecast horizon compared to previous years as interest rates become less favorable. Interest income is projected using the EIU's 12-month EURIBOR estimates, with a spread consistent with Banco CTT's variable rate mortgage structure. | (5.0%) |
| Motor Vehicle Credit | €M | 57.1 | 58.7 | 61.3 | 64.8 | 68.5 | 71.9 | Assumes the fixed-rate yield from 2023 remains stable, in line with Banco CTT disclosures. Volumes grow in line with improving domestic credit growth. | 4.7% |
| Other Loans | €M | 0.5 | 0.4 | 0.4 | 0.4 | 0.4 | 0.4 | Maintains a constant yield spread, reflecting a small, stable portfolio. Growth is modest, following historical trends. | (4.2%) |
| Income on Other IEA | €M | 32.1 | 33.2 | 34.7 | 36.1 | 37.8 | 38.9 | Reflects interest from other interest-earning assets like central bank funds, interbank placements, and debt securities. A constant yield spread is applied based on the five-year historical average. | 3.9% |
| Total Interest Expenses | €M | (12.0) | (12.6) | (13.2) | (14.1) | (14.8) | (15.5) | The average yield over the last three years determines the cost of medium and long-term debt; increasing issuance volumes contribute to higher absolute costs. Deposit costs are calculated using an average ratio of interest-bearing deposits (over the last three years) with a spread over EURIBOR. This repricing is expected to stabilize as interest rates ease. Expenses on other IBL remain relatively low and stable, continuing the trend from 2023. | 5.2% |
| Expense on Debt Securities | €M | (10.6) | (11.2) | (11.7) | (12.5) | (13.1) | (13.8) | | 5.3% |
| Expense on Deposits | €M | (1.2) | (1.3) | (1.4) | (1.5) | (1.5) | (1.6) | | 5.3% |
| Expense on Other IBL | €M | (0.1) | (0.1) | (0.1) | (0.1) | (0.1) | (0.1) | | - |
| Non-Interest Income | €M | 24.9 | 25.7 | 26.6 | 27.6 | 28.5 | 27.6 | Fees and commissions are growing in line with Portugal's credit outlook (for credit-related fees), the expansion of the financial sector (for savings and insurance), and the projected increase in account openings (for accounts/cards). Meanwhile, other non-interest income comes mainly from the Generali partnership, which contributes a fixed payment of EUR 1.8m annually until FY2028. | 2.1% |
| Fees and Commission | €M | 23.1 | 23.9 | 24.8 | 25.8 | 26.7 | 27.6 | | 3.7% |
| Other Non-Interest Income | €M | 1.8 | 1.8 | 1.8 | 1.8 | 1.8 | - | | (100.0%) |
| Provision for Credit Losses | €M | (25.0) | (26.2) | (27.5) | (28.9) | (30.7) | (32.2) | Calculated as a percentage of gross loans, holding the provisioning rate constant in 2023. The absolute value rises in line with the growth in loan volumes. | 5.2% |
| Non-Interest Expenses | €M | (73.8) | (74.2) | (76.8) | (79.8) | (82.9) | (83.7) | These expenses grow at a moderate pace, broadly in line with inflation, reflecting the additional investments in Banco CTT's operations. Personnel expenses increase due to inflation-adjusted salaries and a slight increase in the number of employees. Administrative expenses are expected to remain stable as a percentage of net revenues, offset by ongoing investments in digital banking and customer service. Other expenses remain relatively stable as a percentage of net revenues, with depreciation and amortization in line with asset usage. | 2.6% |
| Staff Costs | €M | (29.3) | (30.1) | (30.8) | (31.4) | (31.9) | (32.5) | | 2.1% |
| General Administrative | €M | (37.4) | (37.1) | (38.8) | (40.8) | (43.0) | (43.2) | | 2.9% |
| Other Expenses | €M | (7.0) | (6.9) | (7.2) | (7.6) | (8.0) | (8.0) | | 2.9% |
| Pre-Tax Income | €M | 17.4 | 14.8 | 16.2 | 18.0 | 19.8 | 18.0 | The improved loan book and controlled costs support modest pre-tax profit growth over the forecast horizon. | 0.6% |

# Appendix 4 - SWOT Analysis for Banco CTT:

**S**

- **Strong Brand Association with CTT:** Benefitting from well established CTT brand which is being trusted by older demographics and rural communities
- **Growth in Customer Deposits & Mortgage Loans:** Historically significant increases demonstrates Banco CTT's ability to attract retail customers
- **Resilient Solvency Position:** High CET1 ratio provides buffer against potential market risk and openness to future strategic options
- **Wide Network and Accessibility:** Ability to leverage large network, especially in regions that may be underserved by larger competitors

**W**

- **Limited Presence in Corporate Banking:** Limited presence in Corporate which could limit growth potential
- **Late to Digital Banking Solutions:** Only 6% market share as Banco CTT has been slow in comparison to portuguese and global competitors
- **High Dependence on Interest Income:** Profitability is heavily dependent on interest income
- **Vulnerability to Credit Risk:** Significant and growing exposure to mortgage sector exposes to associated credit risks

**O**

- **Digital Banking Growth:** Increasing digital banking penetration (58.9% in 2023) opens new potential customer segments and products
- **Growth in Rural Markets:** Unique opportunity through the established CTT network with less competition from larger banks
- **Partnerships (with Insurance):** Partnerships with insurance providers leverages network and brings potentially new customers to the bank points

**T**

- **Intense Competition:** Rise of digital-only banks and Fintechs pose risks for CTT particularly in younger and urban demographics
- **Economic Uncertainties:** Economic outlook remains uncertain, with potential risks economic growth and geopolitical tensions
- **Regulatory Changes:** Upcoming adjustments may increase operational costs (related to capital requirements and liquidity ratios)

# Appendix 5 - Financial Analysis Bank:

| Income Statement (€k) Summary | 2019 | 2020 | 2021 | 2022 | 2023 | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F | CAGR 24-29 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Net Interest Income:** | | | | | | | | | | | | |
| (+) Interest Income: | 29,260 | 44,574 | 55,718 | 74,393 | 98,257 | 91,258 | 89,432 | 93,859 | 99,082 | 104,815 | 106,196 | 3.3% |
| (-) Interest Expense: | 16,559 | 21,401 | 37,374 | 35,885 | 22,067 | 24,893 | 25,707 | 26,608 | 27,583 | 28,539 | 27,646 | 5.2% |
| **Total Net Interest Income:** | **29,260** | **44,574** | **55,718** | **74,393** | **98,257** | **91,258** | **89,432** | **93,859** | **99,082** | **104,815** | **106,196** | **3.1%** |
| Non-Interest Income: | 16,559 | 21,401 | 37,374 | 35,885 | 22,067 | 24,893 | 25,707 | 26,608 | 27,583 | 28,539 | 27,646 | 2.1% |
| **Total Net Revenue:** | **45,819** | **65,975** | **93,092** | **110,278** | **120,324** | **116,151** | **115,139** | **120,466** | **126,665** | **133,354** | **133,842** | **2.9%** |
| **(-) Provision for Credit Losses:** | **(3,054)** | **(10,028)** | **(14,134)** | **(24,719)** | **(24,992)** | **(24,992)** | **(26,177)** | **(27,477)** | **(28,900)** | **(30,687)** | **(32,219)** | **5.2%** |
| **Non-Interest Expenses:** | | | | | | | | | | | | |
| (-) Staff Costs: | (19,428) | (21,806) | (23,034) | (24,871) | (27,867) | (29,344) | (30,136) | (30,769) | (31,354) | (31,918) | (32,493) | 2.1% |
| (-) General Administrative: | (27,498) | (27,152) | (31,035) | (34,523) | (38,794) | (37,449) | (37,122) | (38,840) | (40,838) | (42,995) | (43,152) | 2.9% |
| (-) Other Expenses: | (5,340) | (5,775) | (6,238) | (7,376) | (7,831) | (6,960) | (6,899) | (7,221) | (7,595) | (7,998) | (8,028) | 2.9% |
| **Total Non-Interest Expenses:** | **(52,266)** | **(54,733)** | **(60,307)** | **(66,770)** | **(74,492)** | **(73,753)** | **(74,158)** | **(76,830)** | **(79,787)** | **(82,912)** | **(83,673)** | **2.6%** |
| **Pre-Tax Income:** | **(9,501)** | **1,214** | **18,651** | **18,789** | **20,840** | **17,406** | **14,805** | **16,160** | **17,978** | **19,756** | **17,950** | **0.6%** |
| (-) Taxes: | 1,490 | (979) | (4,552) | (5,828) | (5,055) | (3,655) | (3,109) | (3,394) | (3,775) | (4,149) | (3,770) | |
| (+/-) Profit/Loss of Disc. Business: | - | - | 2,049 | 1,755 | 1,238 | - | - | - | - | - | - | |
| **Net Income:** | **(8,011)** | **235** | **16,148** | **14,716** | **17,023** | **13,751** | **11,696** | **12,766** | **14,203** | **15,607** | **14,181** | **0.6%** |

| Balance Sheet (€M) Summary | 2019 | 2020 | 2021 | 2022 | 2023 | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Net Loans: | 886 | 1,093 | 1,542 | 1,778 | 1,593 | 1,657 | 1,728 | 1,806 | 1,907 | 1,991 | 2,081 |
| Total Assets: | 1,666 | 2,000 | 2,704 | 3,105 | 3,827 | 4,000 | 4,192 | 4,402 | 4,664 | 4,891 | 5,133 |
| Deposits: | 1,284 | 1,688 | 2,122 | 2,280 | 3,106 | 3,253 | 3,415 | 3,592 | 3,814 | 4,004 | 4,208 |
| Total Liabilities & Equity: | 1,666 | 2,000 | 2,704 | 3,105 | 3,827 | 4,000 | 4,192 | 4,402 | 4,664 | 4,891 | 5,133 |
| Book Value: | 211 | 212 | 238 | 253 | 270 | 284 | 296 | 309 | 323 | 339 | 353 |
| Tangible Book Value: | 123 | 122 | 154 | 171 | 188 | 202 | 214 | 227 | 241 | 257 | 271 |
| Risk -Weighted Assets (RWA): | 725 | 793 | 1,036 | 1,176 | 946 | 1,179 | 1,234 | 1,291 | 1,360 | 1,412 | 1,458 |

| Operating Metrics Summary | 2019 | 2020 | 2021 | 2022 | 2023 | 2024E | 2025F | 2026F | 2027F | 2028F | 2029F |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Return on Tangible Common Equity: | (8.6%) | 0.2% | 11.7% | 9.0% | 9.5% | 7.1% | 5.6% | 5.8% | 6.1% | 6.3% | 5.4% |
| Return on Equity: | (5.3%) | 0.1% | 7.2% | 6.0% | 6.5% | 5.0% | 4.0% | 4.2% | 4.5% | 4.7% | 4.1% |
| Return on Assets: | (0.7%) | 0.0% | 0.8% | 0.6% | 0.5% | 0.4% | 0.3% | 0.3% | 0.3% | 0.4% | 0.3% |
| Net Loans / Total Assets: | 53.2% | 54.7% | 57.0% | 57.3% | 41.6% | 41.4% | 41.2% | 41.0% | 40.9% | 40.7% | 40.5% |
| Deposits / Total Liabilities & Equity: | 77.1% | 84.4% | 78.5% | 73.4% | 81.2% | 81.3% | 81.5% | 81.6% | 81.8% | 81.9% | 82.0% |
| Net Loans / Deposits: | 69.0% | 64.8% | 72.7% | 77.9% | 51.3% | 50.9% | 50.6% | 50.3% | 50.0% | 49.7% | 49.4% |
| Reserve Ratio: | 0.4% | 1.5% | 2.0% | 3.0% | 2.9% | 3.6% | 4.2% | 4.8% | 5.3% | 5.9% | 6.4% |
| Net Interest Margin: | 2.6% | 2.7% | 2.6% | 2.8% | 3.0% | 2.4% | 2.3% | 2.3% | 2.3% | 2.3% | 2.3% |
| Average Interest Rate on IEA: | 2.8% | 2.8% | 2.7% | 3.0% | 4.1% | 2.8% | 2.6% | 2.6% | 2.6% | 2.7% | 2.6% |
| Average Interest on IBL: | 0.5% | 0.3% | 0.3% | 0.5% | 1.6% | 0.5% | 0.6% | 0.6% | 0.6% | 0.6% | 0.6% |
| Spread: | 2.3% | 2.6% | 2.4% | 2.5% | 2.5% | 2.3% | 2.0% | 2.0% | 2.0% | 2.1% | 2.0% |
| Net Interest Income / Revenue: | 63.9% | 67.6% | 59.9% | 67.5% | 81.7% | 78.6% | 77.7% | 77.9% | 78.2% | 78.6% | 79.3% |
| Cost to Income: | 114.1% | 83.0% | 64.8% | 60.5% | 61.9% | 63.5% | 64.4% | 63.8% | 63.0% | 62.2% | 62.5% |
| Common Equity Tier 1: | 25.7% | 24.6% | 15.4% | 15.1% | 20.7% | 16.1% | 17.3% | 18.5% | 19.7% | 21.2% | 22.5% |
| Tier 1 Capital Ratio: | 25.7% | 24.6% | 15.4% | 15.1% | 20.7% | 16.1% | 17.3% | 18.5% | 19.7% | 21.2% | 22.5% |
| Total Capital Ratio: | 25.7% | 24.6% | 15.4% | 15.1% | 20.7% | 16.1% | 17.3% | 18.5% | 19.7% | 21.2% | 22.5% |

# Appendix 6 – Valuation:

| Company name | Market Cap. (€k) | β 5yr | β Blume Adj. | NAICS Subsector Name | Debt-to-Equity Ratio | Statutory Tax Rates | β Unlevered | Cash Holdings to EV |
|---|---|---|---|---|---|---|---|---|
| **CTT Correios de Portugal SA** | **678,855** | **0.62** | **0.75** | **Postal Service** | **14.64** | **21%** | **0.06** | **16%** |
| Boa Concept SA | 17,346 | 0.20 | 0.46 | Professional, Scientific, and Technical Services | 0.16 | 25% | 0.41 | 82% |
| BREMER LAGERHAUS-GESELLSCHAFT AG von 1877 | 37,764 | 0.06 | 0.37 | Professional, Scientific, and Technical Services | 2.66 | 35% | 0.14 | 6% |
| MaltaPost plc | 39,025 | 0.60 | 0.73 | Postal Service | 0.06 | 30% | 0.70 | 16% |
| Bpost SA | 404,877 | 0.91 | 0.94 | Couriers and Messengers | 1.26 | 25% | 0.48 | 64% |
| PostNL NV | 535,618 | 0.91 | 0.94 | Postal Service | 4.94 | 26% | 0.20 | 44% |
| Logwin AG SA | 710,648 | 0.24 | 0.49 | Professional, Scientific, and Technical Services | 0.21 | 25% | 0.42 | 76% |
| Oesterreichische Post AG | 2,012,309 | 0.29 | 0.53 | Postal Service | 5.30 | 23% | 0.10 | 3% |
| ID Logistics SAS | 2,582,571 | 0.68 | 0.79 | Truck Transportation | 3.34 | 25% | 0.22 | 8% |
| Logista Integral SA | 4,015,723 | 0.58 | 0.72 | Professional, Scientific, and Technical Services | 0.44 | 25% | 0.54 | 5% |
| Compagnie du Cambodge SA | 6,686,141 | 0.60 | 0.73 | Professional, Scientific, and Technical Services | 0.00 | 25% | 0.73 | 32% |
| InPost SA | 8,538,044 | 1.02 | 1.01 | Couriers and Messengers | 5.13 | 25% | 0.21 | 2% |
| Poste Italiane SpA | 18,782,404 | 0.93 | 0.95 | Credit Intermediation and Related Activities | 8.54 | 24% | 0.13 | 14% |
| Deutsche Post AG | 42,430,091 | 1.03 | 1.02 | Postal Service | 0.99 | 30% | 0.60 | 5% |

Pure play approach Beta: a Cash Adjustment for Mail and Express and Parcels Business Units has been performed due to the high liquidity detained by CTT Group.

| Industry | Average Cash Holdings to EV | CTT's β Unlevered Cash Adj. by segment | CTT's β Levered by segment |
|---|---|---|---|
| Mail | 17% | 0.49 | 0.89 |
| E&P | 24% | 0.54 | 0.99 |

| Mail FCFE | Unit | 2025F | 2026F | 2027F | 2028F | 2029F | TV |
|---|---|---|---|---|---|---|---|
| NOPAT | €k | -5,899 | -6,251 | -11,512 | -17,730 | -23,964 | |
| (+) D&A | €k | 35,691 | 33,735 | 31,887 | 30,139 | 28,487 | |
| (-) CapEx | €k | 38,180 | 43,931 | 37,875 | 23,050 | 18,147 | |
| (-) Δ NWC | €k | 5,050 | 1,328 | 3,623 | 3,520 | 2,093 | |
| (-) Interest Expense * (1-T) | €k | 6,571 | 7,063 | 7,413 | 7,917 | 8,329 | |
| (+) Net Borrowings | €k | 10,197 | 10,220 | 6,826 | 10,402 | 13,308 | |
| FCFE | €k | -8,543 | -13,274 | -19,236 | -7,865 | -5,586 | -64,487 |
| PV(FCFE) | €k | -8,543 | -12,216 | -16,291 | -6,129 | -4,006 | -46,245 |
| **Equity Value** | **€k** | **-93,430** | | | | | |

| BCTT FCFE | Unit | 2025F | 2026F | 2027F | 2028F | 2029F | TV |
|---|---|---|---|---|---|---|---|
| Net Income | €k | 11,696 | 12,766 | 14,203 | 15,607 | 14,181 | |
| FCFE | €k | 11,696 | 12,766 | 14,203 | 15,607 | 14,181 | 132,653 |
| PV(FCFE) | €k | 11,696 | 11,329 | 11,184 | 10,902 | 9,903 | 92,635 |
| Equity Value | €k | 147,649 | | | | | |
| **Equity Value (CTT 91.29% stake** | **€k** | **134,788** | | | | | |

| E&P FCFE | Unit | 2025F | 2026F | 2027F | 2028F | 2029F | TV |
|---|---|---|---|---|---|---|---|
| NOPAT | €k | 53,160 | 63,986 | 85,170 | 96,881 | 106,977 | |
| (+) D&A | €k | 14,139 | 13,364 | 12,632 | 11,939 | 11,285 | |
| (-) CapEx | €k | 18,817 | 22,126 | 19,314 | 25,770 | 32,831 | |
| (-) Δ NWC | €k | -2,191 | 3,638 | 2,462 | 1,939 | 5,059 | |
| (-) Interest Expense * (1-T) | €k | 4,319 | 4,643 | 4,873 | 5,204 | 5,475 | |
| (+) Net Borrowings | €k | 13,595 | 13,627 | 9,101 | 5,201 | 4,436 | |
| FCFE | €k | 47,935 | 46,107 | 61,003 | 59,210 | 55,153 | 902,533 |
| PV(FCFE) | €k | 38,658 | 33,763 | 46,964 | 44,536 | 38,439 | 617,389 |
| Equity Value | €k | 819,749 | | | | | |
| **Equity Value (CTT 75% stake)** | **€k** | **614,812** | | | | | |

| FS FCFE | Unit | 2025F | 2026F | 2027F | 2028F | 2029F | TV |
|---|---|---|---|---|---|---|---|
| NOPAT | €k | 19,838 | 14,593 | 14,843 | 15,269 | 15,364 | |
| (+) D&A | €k | 122 | 115 | 109 | 103 | 97 | |
| (-) CapEx | €k | 161 | 158 | 156 | 154 | 154 | |
| (-) Δ NWC | €k | -4,174 | 2,917 | 218 | 200 | 74 | |
| (-) Interest Expense * (1-T) | €k | 0 | 0 | 0 | 0 | 0 | |
| (+) Net Borrowings | €k | 0 | 0 | 0 | 0 | 0 | |
| FCFE | €k | 23,973 | 11,633 | 14,578 | 15,017 | 15,233 | 205,292 |
| PV(FCFE) | €k | 23,973 | 10,722 | 12,384 | 11,756 | 10,992 | 148,131 |
| **Equity Value** | **€k** | **217,957** | | | | | |

| RE Market Value | Unit | 2025F | 2026F | 2027F | 2028F | 2029F |
|---|---|---|---|---|---|---|
| Market Value | €k | 153,441 | 160,346 | 163,553 | 166,824 | 170,160 |
| House Price Index (PT) | €k | 234,910 | 245,480 | 250,390 | 255,397 | 260,505 |
| YoY | % | 5% | 4% | 2% | 2% | 2% |
| Inflation | % | | | 2% | 2% | 2% |
| Equity Value | €k | 153,441 | | | | |
| **Equity Value (CTT 73.7% stake)** | **€k** | **113,086** | | | | |

# Appendix 7 - Alternative Valuation Methods:

**Banco CTT - Precedent Transaction Analysis (in € Million):**

| Target Name | Target Industry | Target Nation | Value of Equity | Tangible Book Value | Net Income | P/TBV | ROE |
|---|---|---|---|---|---|---|---|
| Euroclear Holding SA/ | Financials | Belgium | 9,247.97 | 4,206.80 | 462.55 | 2.20 | 19.99 |
| Daphne 3 SpA | Financials | Italy | 2,500.00 | 2,122.76 | 83.72 | 1.18 | 29.86 |
| Topdanmark A/S | Financials | Denmark | 4,533.96 | 931.16 | 140.92 | 4.87 | 32.17 |
| EQT AB | Financials | Sweden | 34,024.70 | 7,281.50 | 139.20 | 4.67 | 244.43 |
| Protector Forsikring AS | Financials | Norway | 1,732.47 | 4,175.22 | 128.01 | 0.41 | 13.53 |
| VeloBank SA | Financials | Poland | 246.91 | 952.13 | 88.54 | 0.26 | 2.79 |
| Mandatum Oyj | Financials | Finland | 1,982.10 | 1,400.15 | 160.50 | 1.42 | 12.35 |
| Hoist Finance AB | Financials | Sweden | 364.94 | 4,255.19 | 64.00 | 0.09 | 5.70 |
| Totens Sparebank | Financials | Norway | 123.78 | 1,129.42 | 26.14 | 0.11 | 4.74 |
| Maxmimum | | | 34,024.70 | 7,281.50 | 462.55 | 4.87 | 244.43 |
| 75th Percentile | | | 4,533.96 | 4,206.80 | 140.92 | 2.20 | 29.86 |
| **Median** | | | **1,982.10** | **2,122.76** | **128.01** | **1.18** | **13.53** |
| 25th Percentile | | | 364.94 | 1,129.42 | 83.72 | 0.26 | 5.70 |
| Minimum | | | 123.78 | 931.16 | 26.14 | 0.09 | 2.79 |
| | | | | | | **Equity Value** | |
| **Banco CTT** | | | **270.02** | **188.12** | **17.02** | **221.55** | **214.68** |

# Appendix 8 - Sensitivity Analysis:

**Banco CTT Sensitivity Analysis**

| Perpetuity Growth Rate \ Cost of Equity | 11% | 11.50% | 12% | 12.7% | 13% | 13.50% | 14% |
|---|---|---|---|---|---|---|---|
| 2.3% | 175.61 | 167.18 | 159.60 | 150.32 | 146.54 | 140.87 | 135.67 |
| 2.2% | 174.26 | 165.98 | 158.54 | 149.41 | 145.69 | 140.10 | 134.98 |
| 2.1% | 172.93 | 164.81 | 157.50 | 148.52 | 144.86 | 139.35 | 134.29 |
| 2.0% | 171.64 | 163.67 | 156.48 | 147.65 | 144.04 | 138.61 | 133.62 |
| 1.9% | 170.37 | 162.55 | 155.48 | 146.79 | 143.23 | 137.88 | 132.97 |
| 1.8% | 169.14 | 161.45 | 154.51 | 145.95 | 142.44 | 137.17 | 132.32 |
| 1.7% | 167.93 | 160.37 | 153.54 | 145.12 | 141.67 | 136.47 | 131.68 |

| Domestic Credit Growth \ Euribor 12 M Average | 1.75% | 2.00% | 2.25% | 2.50% | 2.75% | 3.00% | 3.25% |
|---|---|---|---|---|---|---|---|
| 3.3% | 171.67 | 181.04 | 190.40 | 199.76 | 209.12 | 218.48 | 227.84 |
| 2.8% | 154.47 | 163.49 | 172.51 | 181.53 | 190.55 | 199.58 | 208.60 |
| 2.3% | 138.10 | 146.79 | 155.48 | 164.18 | 172.87 | 181.56 | 190.25 |
| 1.8% | 122.53 | 130.90 | 139.28 | 147.65 | 156.02 | 164.40 | 172.77 |
| 1.3% | 107.73 | 115.79 | 123.86 | 131.92 | 139.99 | 148.05 | 156.12 |
| 0.8% | 93.66 | 101.43 | 109.20 | 116.96 | 124.73 | 132.50 | 140.27 |
| 0.3% | 80.30 | 87.78 | 95.26 | 102.74 | 110.22 | 117.70 | 125.18 |

A sensitivity analysis was performed to better grasp how the different segments change when incorporating their main sources of risk as well as the effect of changes in the cost of equity and perpetuity growth rate.

**Banco CTT |** Just like the FS segment, Banco CTT is also exposed to market conditions, and thus, a stress test on EURIBOR 12M Average rates alongside Domestic Credit Growth was computed.

Overall, the valuation is shown to be robust and even when subjected to stress testing, our recommendation remains unaltered.

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Recommendation System

| Level of Risk | SELL | REDUCE | HOLD/NEUTRAL | BUY | STRONG BUY |
|---|---|---|---|---|---|
| High Risk | 0%≤ | >0% & ≤10% | >10% & ≤20% | >20% & ≤45% | >45% |
| Medium Risk | -5%≤ | >-5% & ≤5% | >5% & ≤15% | >15% & ≤30% | >30% |
| Low Risk | -10%≤ | >-10% & ≤0% | >0% & ≤10% | >10% & ≤20% | >20% |

**Disclosure 2 – AI Disclaimer:**

This project was developed with strict adherence to the academic integrity policies and guidelines set forth by ISEG, Universidade de Lisboa. The work presented herein is the result of my own research, analysis, and writing, unless otherwise cited. In the interest of transparency, I provide the following disclosure regarding the use of artificial intelligence (AI) tools in the creation of this thesis/internship report/project:

I disclose that AI tools were employed during the development of this thesis as follows:

- AI-based research tools were used to assist in the literature review and data collection.
- AI-powered software was utilized for data analysis and visualization.
- AI-powered software was utilized for translating the abstract into Portuguese
- Generative AI tools were consulted for brainstorming and outlining purposes. However, all final writing, synthesis, and critical analysis are my own work. Instances where AI contributions were significant are clearly cited and acknowledged.

Nonetheless, I have ensured that the use of AI tools did not compromise the originality and integrity of my work. All sources of information, whether traditional or AI-assisted, have been appropriately cited in accordance with academic standards. The ethical use of AI in research and writing has been a guiding principle throughout the preparation of this thesis.

I understand the importance of maintaining academic integrity and take full responsibility for the content and originality of this work.

Alexander Lorenzl, June 30, 2025

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