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ENSEMBLE LEARNING AND NLP FOR M&A TARGET SELECTION: THE CTT CASE.

LORENZO PIROLA

JULY - 2025

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VICTOR BARROS

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Resumo

O presente estudo investiga a aplicação de técnicas de aprendizagem automática para prever alvos de fusões e aquisições (M&A), utilizando o sector da logística, e especificamente o caso da aquisição da Cacesa pelos CTT, como um contexto real. Embora o processo de decisão em M&A seja frequentemente caracterizado pela complexidade e por factores específicos da empresa, a crescente acessibilidade de dados financeiros estruturados e de informação textual não estruturada está a criar novas oportunidades para uma análise sistemática. Com base no Equity Research dos CTT, este estudo propõe uma metodologia que combina indicadores quantitativos e caraterísticas textuais para desenvolver modelos preditivos capazes de identificar prováveis candidatos a aquisições. A aplicação de um quadro de avaliação orientado para o lucro assegura o alinhamento com critérios práticos de decisão. Os resultados indicam que estes modelos aumentam efetivamente a precisão da seleção de alvos, sublinhando a sua relevância para a análise de fusões e aquisições. Embora reconhecendo as restrições impostas pelas limitações de dados, particularmente em relação às empresas privadas, o estudo destaca a promessa de metodologias orientadas por AI para facilitar avaliações estratégicas voltadas para o futuro. Este trabalho fornece informações úteis para os profissionais da indústria e representa uma contribuição significativa para a adoção mais ampla da análise preditiva nas estratégias de aquisição de empresas.

JEL: G34; C55; C63; C88.

Palavras-chave: Mergers & Acquisitions (M&A); Target Selection; Profit-driven Ensemble Learning; FinBERT; Equity Research.

Abstract

The present study investigates the application of machine learning techniques to predict merger and acquisition (M&A) targets, using the logistics sector, and specifically the case of CTT's acquisition of Cacesa, as a real-world context. Although the decision-making process in M&A is frequently characterized by complexity and firm-specific factors, the increasing accessibility of structured financial data and unstructured textual information is creating new opportunities for systematic analysis. Drawing upon the Equity Research of CTT, this study proposes a methodology that combines quantitative indicators and text-based features to develop predictive models capable of identifying likely acquisition candidates. The application of a profit-oriented evaluation framework ensures alignment with practical decision-making criteria. The findings indicate that these models effectively enhance target screening accuracy, underscoring their relevance to M&A analysis. While acknowledging the constraints imposed by data limitations, particularly regarding private companies, the study highlights the promise of AI-driven methodologies in facilitating forward-looking strategic evaluations. This work provides actionable insights for industry practitioners and represents a significant contribution to the broader adoption of predictive analytics in corporate acquisition strategies.

JEL: G34; C55; C63; C88.

Keywords: Mergers & Acquisitions (M&A); Target Selection; Profit-driven Ensemble Learning; FinBERT; Equity Research.

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To my friend Andrea, with whom I chose to take on this adventure: thank you for walking this path with me.

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Abbreviations

E&P	Express & Parcels
M&A	Mergers & Acquisitions
AI	Artificial Intelligence
ML	Machine Learning
NLP	Natural Language Processing
BERT	Bidirectional Encoder Representations from Transformers
UMAP	Uniform Manifold Approximation and Projection
SMOTE	Synthetic Minority Over-sampling Technique
FPR	False Positive Rate
TPR	True Positive Rate

Disclosures and Disclaimers

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Lorenzo Pirola, June 2025

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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%

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1 Introduction

Mergers and acquisitions (M&A) are relevant across several sectors, as a mechanism of inorganic growth. Numerous examples can be found, from business diversification to expansion to other markets. The recent deals of CTT group are an example. The Portuguese company expanded its activities of Express & Parcels (E&P) to Spain through an acquisition and a partnership. Specifically, CTT acquired Compañía Auxiliar al Cargo Express S.A. (Cacesa) and established a joint venture with DHL. The market was aware of a potential move from the company, but the target was unknown.

A similar scenario can be anticipated in the near future. According to a report by JB Capital Markets[1], CTT is expected to hold approximately €120M in excess cash. This figure is derived from a straightforward analysis of the company's Net Debt to EBITDA ratio, which CTT's investor relations has consistently indicated should remain around 2x. Given this financial position, it is reasonable to expect that CTT will pursue further expansion, particularly in strategically significant areas such as the E&P segment, which continues to demonstrate strong growth potential. This course of action is consistent with the company's long-term strategic vision.

As Damodaran (2018) observes, acquisitions can become a company's "addiction", and once a corporation starts conducting mergers and acquisitions, it frequently continues.

In this context, considering CTT’s financial strength and previous activities, further acquisitions appear likely, even if no specific targets have yet emerged in the eyes of investors.

Consequently, the question remains as to which company will be targeted. The ability to predict targets remains uncertain.

[1] https://www.jbcm.com/

Although M&A activity is broad and highly variable, recent advances in artificial intelligence, particularly machine learning and Natural Language Processing (NLP), offer promising tools for generalizing and predicting potential acquisition targets. In contrast to subsequent phases of the M&A process, which typically necessitate access to proprietary, company-specific data, the target identification stage presents an opportunity to leverage structured and available datasets. This creates the possibility for data-driven approaches, particularly those supported by modern technologies, to enhance decision-making at this critical juncture.

This thesis seeks to assess whether the target selection process in M&A can be effectively formalized and generalized across industries, given the demonstrated potential of artificial intelligence (AI) to significantly improve the accuracy of such analyses. It aims to explore the benefits of applying this AI-driven approach within a specific industry, geographic, and temporal context, particularly in identifying the most influential variables driving acquisition decisions.

The findings of this study demonstrate that a combination of financial indicators, specifically Total Revenue (Size), Return on Assets (Profitability), and Revenue CAGR over three years (Growth), alongside text-based features, yields a robust foundation for machine learning models in the context of M&A target prediction. This research underscores the practical applicability of AI-driven methodologies within the logistics industry, using the case of CTT as a real-world example to validate the model's effectiveness in identifying likely acquisition targets.

2 Literature Review

2.1 M&A Process: Drivers

M&A activity is found to be significantly influenced by (i) the financial strength of the firm, (ii) managerial behavior, and (iii) external macroeconomic factors.

Firms with ample liquidity are more inclined to pursue acquisitions, even when such investments result in substandard post-acquisition performance (Harford, 1999). This finding, further reinforced by more recent studies (Erel, Jang, Minton, & Weisbach, 2019), provides important support for the thesis, suggesting that CTT's financial position increases the likelihood that it will engage in acquisitions.

Overconfident CEOs have been observed to exhibit a propensity towards acquisitive behavior, particularly in circumstances where internal financing is available, a tendency that frequently culminates in transactions that are detrimental to the firm's value (Malmendier & Tate, 2008). Mis-valuation also plays a critical role, with overvalued firms being more likely to acquire less overvalued targets using stock, particularly during sector-level overvaluation, and merger intensity being largely driven by short-term valuation errors rather than fundamentals (Rhodes-Kropf, Robinson, & Viswanathan, 2005).

At the macro level, the phenomenon of merger waves is triggered by industry-specific economic, regulatory, or technological shocks. It has been demonstrated that these waves only materialize when there is sufficient capital liquidity (Harford, 2005). Moreover, policy uncertainty exerts a substantial inhibitory effect on M&A activity, particularly in instances where it pertains to monetary, fiscal, or regulatory issues, as firms often postpone or discontinue transactions due to the impact of real option effects (Bonaime & Gulen, 2018).

Recent studies have expanded the M&A literature to include ESG and technological dimensions.

The concept of Green M&A has emerged as a response to environmental responsibilities, particularly among heavy polluters. However, the effectiveness and authenticity of such transformations remain mixed (Liang, Li, Luo, & Li, 2022).

Digital transformation has been demonstrated to play a pivotal role in facilitating mergers and acquisitions (M&A) by reducing internal organizational costs (Tu & He, 2023). Furthermore, it has been shown to enhance the completion rate of cross-border M&A, particularly for innovation-focused firms and those encountering financial constraints (Wang, Yuan, & Zhang, 2024). These findings underscore the mounting significance of non-traditional factors, such as sustainability and digitalization, in shaping contemporary M&A strategies.

2.2 M&A Process: Consequences

In addition to the factors influencing M&A activity, considerable effort has been devoted to understanding synergies and post-acquisition performance (Healy, Palepu, & Ruback, 1992).

One critical factor in cross-border transactions is cultural compatibility. Greater cultural distance between countries, particularly with regard to dimensions such as trust, hierarchy and individualism, is associated with lower M&A volume and weaker combined announcement returns (Ahern, Daminelli, & Fracassi, 2012). This highlights how cultural frictions can undermine deal success.

Another key determinant of performance is the acquirer's managerial ability. Firms led by high-ability managers generate significantly higher abnormal returns in M&A transactions, particularly in stock-financed public target deals. This is explained by their ability to select targets with higher intangible assets and unrealized growth potential while avoiding financially distressed firms with a high risk of bankruptcy (Dong & Doukas, 2021).

A significant proportion of the existent literature on M&A has focused on publicly traded firms, emphasizing both market-based drivers and the broader impact on stakeholders. It has been demonstrated that acquisitions are frequently driven by stock market dynamics. Specifically, overvalued firms utilize inflated equity to acquire less overvalued targets (Shleifer & Vishny, 2003).

Beyond valuation motives, Corporate Social Responsibility (CSR) has also been linked to M&A outcomes; acquirers with high CSR profiles tend to generate superior announcement returns, post-merger performance, and deal completion rates, supporting the stakeholder value maximization perspective (Deng, Kang, & Low, 2013).

Furthermore, it is evident that the acquirer returns vary considerably based on the target type and the structure of the deal. It has been demonstrated that bidders accrue benefits when acquiring private firms or subsidiaries, and conversely incur losses when targeting public firms, particularly when stock is employed (Fuller, Netter, & Stegemoller, 2002). This finding suggests that private acquisitions yield liquidity discounts and governance benefits that are not present in public deals.

2.3 Text-Based Information: NLP Application on M&A

The first application of Natural Language Processing (NLP) in M&A uses text-based measures of product similarity to assess how asset complementarities and market competition influence merger incentives and post-acquisition outcomes (Hoberg & Phillips, 2010). Recent applications of NLP have expanded into cultural analysis and due diligence. One study uses word embeddings to build a machine learning–based culture dictionary, showing that corporate culture influences firm performance and plays a role in merger activity and post-deal cultural alignment (Li, Mai, Shen, & Yan, 2020). Another study applies NLP to assess M&A capability, finding that firms with greater acquisition experience and structured M&A processes achieve better long-term performance (Vinocur, Kiymaz, & Loughry, 2022). Leveraging NLP allows researchers to enhance M&A analysis by incorporating unstructured data, such as corporate disclosures and strategy statements. This is a significant development as, previously, such data were either difficult or impossible to utilize with traditional approaches.

Other NLP applications focus on target selection and will be discussed in the following paragraph.

2.4 M&A: Target Selection Literature

Early research on M&A target predictions primarily relied on financial ratios to identify common characteristics among targets (Palepu, 1986). However, these models may be inadequate for developing effective investment strategies. With advances in machine learning and the growing integration of AI in analysis, researchers have expanded the range of variables beyond traditional financial metrics. This has led to greater accuracy, as well as significant savings in time and resources. While findings vary, the most recent studies focus on broadening the predictive toolkit for identifying potential M&A targets.

There is country-specific research. For instance, in the French context, target firms tend to exhibit high growth potential, unused debt capacity, limited liquidity and low value creation, which makes them appealing to acquirers seeking synergies or strategic repositioning (Meghouar & Ibrahimi, 2020). Qualitative signals, such as the language used in shareholder letters, have also been shown to be predictive of a firm's openness to acquisition (Parungao, Galido, Suazo, & Parungao, 2022). News-based sentiment and topic features now outperform traditional financial indicators, highlighting the predictive value of market perception (Hajek & Henriques, 2024). Similarly, language from annual reports, especially when analyzed using finance-specific word embeddings, provides substantial additional predictive power (Katsafados, Leledakis, Pyrgiotakis, Androutsopoulos, & Fergadiotis, 2023). The combination of structured financial data and text-based features from company descriptions and press releases achieves the highest accuracy.

A common limitation across the cited studies is their predominant focus on publicly listed companies, despite the significant role private firms play in the M&A landscape. This study contends that financial ratios remain fundamental in target selection, especially when evaluating private companies. However, the integration of text-based information can significantly enhance the analysis by capturing qualitative signals that financial data alone may overlook. Additionally, adopting a sector-specific perspective is crucial, as M&A dynamics can vary widely across industries. Text analysis enables a deeper understanding of the strategic rationale behind deals, allowing for more nuanced assessments beyond traditional financial indicators.

Table 1 summarizes the characteristics of the studies referenced in the preceding paragraph, providing a clearer and more accessible overview of the relevant literature.

Table 1 – Literature Review: Machine Learning Applications on M&A Target Selection

Authors (Year)	Obs. time	Industry	Geographic Area	Financial Features	Text-based Features	Filters	Method	Accuracy
Meghouar and Ibrahimi (2020)	2001-2007	All	France	Firm size, Firm performance, Growth-resource imbalance, Market Under/Over-valuation, Dividend policy, Free Cash Flow, Growth opportunities, Industry Disturbance, Ownership structure (Total: 21)	None	Only large firms (Deal Value > €100M)	Logistic Regression	Acc. = 0.894
Parungao, Galido, Suazo, and Parungao (2022)	2005-2019	Pharmaceuticals / Chemicals, Finance, Energy, Consumer Goods	America & Europe	None	Firm's letters to Shareholders	Only publicly traded firms with Market Cap. > $1B	Decision Tree	Acc. = 0.670
Hajek and Henriques (2024)	2020-2021	All	US & UK	Firm size, Growth-resource imbalance, Market Under/Over-valuation, Dividend policy, Free Cash Flow, Profitability, Firm age, Leverage, Liquidity, Price to Earnings, Ownership structure (Total: 35)	News-based sentiment and topic detection	Only publicly traded firms (Deal Value > $100M)	Profit-driven Ensemble learning	Acc. = 0.930
Katsafados, Leledakis, Pyrgiotakis, Androutsopoulos and Fergadiotis (2023)	1994-2016	Banks	US	Cost-to-Income, ROA, Capital Strength, Loans, Market Power, Asset Quality, Non-interest Income, Deposits, Market Variables (Total: 12)	Annual Reports	Only publicly traded bidders on NYSE, AMEX, or NASDAQ. Only majority stake acquisitions.	Mixed (Logistics regression; Support Vector Machines; Random Forest; Multilayer Perceptron)	AUC = 0.690
This study (2025)	2014-2023	Logistics	Europe	Firm's size, Profitability, Efficiency, Liquidity, Capital Structure, Growth (Total: 17)	Business Description & Products Description	Only majority stake acquisitions.	Profit-driven Ensemble learning	

3 Data & Methodology

This study presents a 10-year analysis of mergers and acquisitions (M&A) activity in the logistics sector. The scope of the study includes the following industry segments in Europe: (i) Courier, Postal, Air Freight & Land-based Logistics; (ii) Marine Freight & Logistics; and (iii) Ground Freight & Logistics.

Two initial datasets were sourced from Refinitiv: (i) one containing all companies operating in the specified industries, and (ii) another detailing all M&A deals involving these sectors. The datasets were then cross-referenced using company identifiers (IDs) to identify which companies were involved in M&A transactions. This process enabled the creation of the final dataset, in which each company was assigned an annual Boolean variable designated 'Target', equal to 1 if the company was the target of a majority stake acquisition during that year, and 0 otherwise. This labeling defined the positive and negative classes for the classification task across all years in the dataset.

The finalized dataset encompasses the period from 2014 (FY-9) to 2023 (FY0), and incorporates comprehensive firm-level information. Specifically, it comprises 17 financial indicators (Table 2), which include measures of size, profitability, liquidity, capital structure, efficiency, and growth. The selection of financial features was guided by the objective of capturing a comprehensive representation of each firm's characteristics within the dataset, given the limited disclosure typical of privately held companies. In addition, the dataset incorporates text-based business and product descriptions, which were converted into 768-dimensional numeric vectors using FinBERT[2].

[2] https://huggingface.co/yiyanghkust/finbert-tone

Table 2 – Financial Features

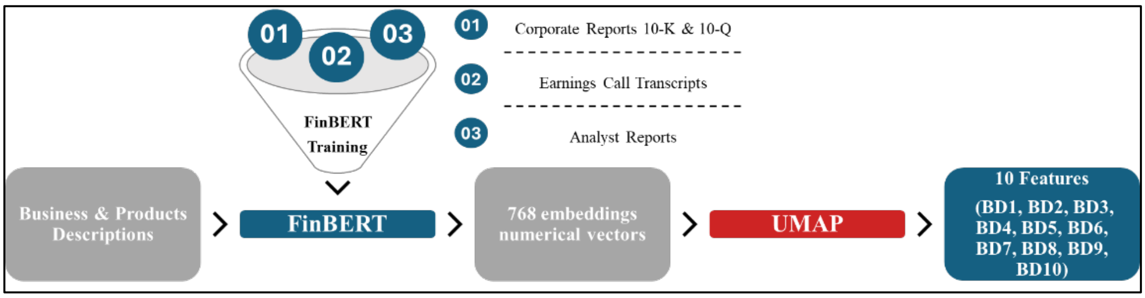
#	Size	Profitability	Efficiency	Liquidity	Capital Structure	Growth
1	Log (Total Revenue)	EBIT Margin	Asset Turnover	Current ratio	Debt to Equity	Revenue CAGR (past 3yrs)
2	Log (Total Assets)	EBITDA Margin	Working Capital to Sales	Quick ratio	Debt to Assets	EBIT CAGR (past 3 yrs)
3		Net Income Margin		Cash Ratio	Long Term Debt to Capital	
4		ROCE				
5		ROA				

3.1 Feature Engineering

3.1.1 FinBERT application (NLP)

FinBERT is a specialized natural language processing model based on BERT (Bidirectional Encoder Representations from Transformers). The software has been trained on financial texts and has been shown to be particularly adept at capturing the nuances and specialized terminology of financial language (Huang, Wang & Yang, 2022). It was deemed imperative to apply a dimensionality reduction technique, such as UMAP (Uniform Manifold Approximation and Projection), in light of the high dimensionality that resulted from the FinBERT embeddings. This approach helps mitigate the risk of overfitting caused by an excessive number of features prior to training the machine learning model. The selection of UMAP, configured with 5 components and 15 neighbours, was made on the basis of its demonstrated computational efficiency and its ability to preserve both the global and local structures of the original high-dimensional dataset during the process of clustering (Hajek & Henriques, 2024).

Figure 1 – FinBERT & UMAP



3.1.2 Missing Data Handling

Given that the dataset primarily comprises private companies, the presence of missing data poses a significant challenge. To ensure data reliability, all company-year records with missing values were excluded. As a result, the sample size decreased from an initial 6,247 company-year observations to the figures reported in Table 3. It is evident that more complete records were available in recent years due to enhanced data availability. Furthermore, for target companies with only a single missing value, the median imputation method was employed to maximize the retention of the already limited positive class. Lastly, due to missing data from Refinitiv for Compañía Auxiliar al Cargo Express S.A. (Cacesa), the Quick Ratio was imputed using company information previously analyzed for the Equity Research report, in order to ensure Cacesa's inclusion in the dataset for the purposes of this study.

3.1.3 Training/Test Data Split & Class Imbalance

In order to ensure temporal validity and to prevent the occurrence of look-ahead bias, the dataset was split chronologically. The model was trained on financial data spanning the period from FY-9 to FY-1, and was tested exclusively on the most recent period, FY0. This configuration reflects a realistic forecasting scenario, consistent with the intended application of the model, to simulate the perspective of CTT prior to its acquisition of Cacesa, by identifying probable M&A targets based on observable financial and textual signals. In a broader sense, the model's objective is to extract generalizable insights and robust predictive patterns within the logistics industry, thus offering a framework for the prospective target screening in similar strategic contexts. Fiscal year FY-3 was excluded from training due to the absence of positive class (Targets) examples, likely caused by the disruptions of the COVID-19 pandemic.

The empirical analysis of the panel data revealed a pronounced class imbalance, with the positive class consistently representing less than 1% of the sample. To address this issue, a hybrid resampling strategy was applied to the training data, combining both oversampling and undersampling techniques. Specifically, undersampling was conducted using Condensed Nearest Neighbours (CNN), while Borderline-SMOTE, a variant of the Synthetic Minority Over-sampling Technique that focuses on borderline instances, was employed to generate synthetic samples of the minority class. This method (Han, Wang, & Mao, 2005), focuses on samples that are located in proximity to the decision boundary, as these are often considered more informative and are more susceptible to misclassification. The combined approach resulted in a more balanced distribution of positive and negative cases within the training set, thereby facilitating more robust model training.

Table 3 – Descriptive Statistics & Class Imbalance

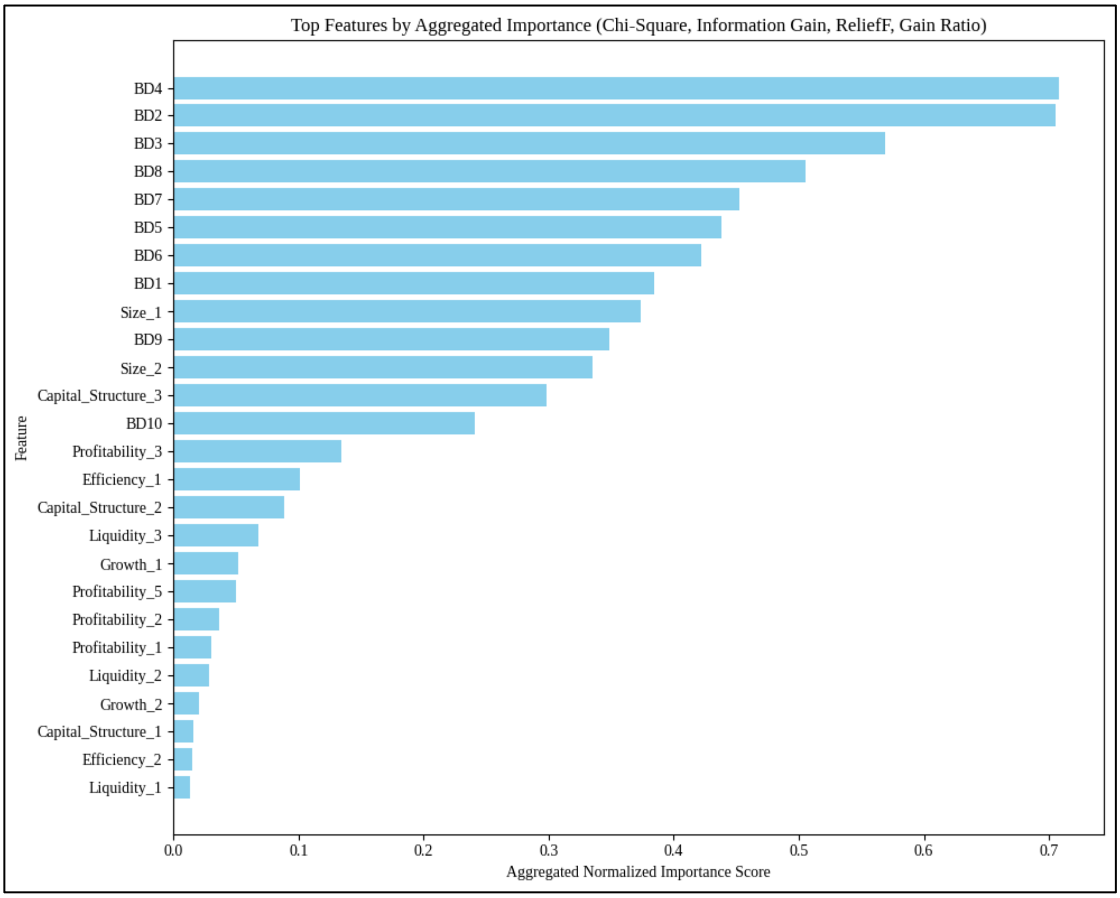
M&A data panel | Company-year obs.										
Year	FY-0	FY-1	FY-2	FY-3	FY-4	FY-5	FY-6	FY-7	FY-8	FY-9
Obs. after missing data handling	2,486	2,293	2,128	1,955	1,820	1,606	1,535	1,420	1,207	944
M&A target	7	8	10	0	5	6	8	4	6	3
Positive Class (%)	0.3%	0.3%	0.5%	0%	0.3%	0.4%	0.5%	0.3%	0.5%	0.3%

3.1.4 Feature Selection via Aggregate Importance Method

To enhance model interpretability and performance, a feature elimination strategy using multiple statistical and information-theoretic criteria was implemented. Feature importance was initially computed using four distinct methods: Information Gain, Chi-Squared statistics, ReliefF and Gain Ratio. These scores were merged into a combined feature importance matrix to enable a comprehensive assessment of feature relevance across multiple dimensions. From this combined matrix, the top 20 features were selected (Figure 2). This elimination approach respects guidelines of previous studies (Hajek & Henriques, 2024).

As a result of the elimination process, seven features were excluded from the model: Profitability_4, Liquidity_1, Efficiency_2, Capital_Structure_1, Growth_2, Liquidity_2, and Profitability_1.

Figure 2 – Feature Importance



3.2 Profit-driven Ensemble Model: Description & Application

The profit-driven ensemble method combines the outputs of multiple base models in order to enhance predictive performance. Base learner models (Table 4) were chosen following previous studies findings (Hajek & Henriques, 2024). The aim is to maximize financial gain by leveraging the strengths of each model while taking into account the economic value of the predicted outcomes. The profit function is central to this approach, as it quantifies the expected monetary gain or loss from the model's predictions.

$$Profit = \pi_1 \cdot b_1 \cdot TPR - \pi_0 \cdot c_0 \cdot FPR$$

Π_1 (Π_0) is the proportion of positive (negative) class in the population;
TPR: True Positive Rate;
FPR: False Positive Rate;
b_1: the benefit of correctly identifying a True Positive;
c_0: the cost of a False Positive.

A high b_1/c_0 ratio encourages the model to favour identifying targets, potentially increasing false positives. Therefore, careful calibration of these parameters is essential for balancing precision and recall in a way that reflects real-world costs and benefits.

In related work, b_1 and c_0 values were estimated using abnormal stock returns for listed M&A targets to derive a literature-informed benchmark for b_1/c_0 (Hajek & Henriques, 2024). However, this study shifts the context to private companies, requiring a different economic frame. For investors, such as private equity or venture capital firms, the benefit (b_1) can be interpreted as the return on a successful investment following the early identification of a target. The cost (c_0) includes expenses incurred when investigating false leads, such as due diligence, legal work and opportunity cost.

4 Results

This section presents the results of the study, which have been structured along four main analytical dimensions.

Primarily, the predictive performance of the models is evaluated using standard statistical metrics, complemented by an economic, profit-based evaluation approach. Secondly, the robustness of the model is assessed through a bootstrapping procedure, thereby demonstrating its stability and ability to handle class imbalance across a large number of randomized samples. Collectively, these initial two points emphasize the extensive applicability and replicability of machine learning models in the context of M&A target prediction, a field in which class imbalance remains a persistent challenge.

Thirdly, the investigation of feature importance is conducted through the utilization of bootstrapped importance distributions, thereby unveiling the variables that exert a consistent influence on the model's predictions. This analysis underscores the significance of text-based features and identifies three financial variables, being Size (Total Revenue), Profitability (ROA), and Growth (Revenue CAGR over 3 years), as particularly robust predictors.

Finally, the fourth dimension explores the real-world applicability of the approach through a retrospective analysis of CTT's acquisition of Cacesa. This case study is employed to address the central motivating question of the research, with the aim of demonstrating the model's potential to support strategic decision-making in actual M&A scenarios.

4.1 Ensemble Method Results

The application of the profit-driven ensemble approach resulted in a substantially higher level of performance in predicting M&A targets when compared with individual models. The confusion matrix (Figure 3) illustrates a balanced performance, with a true positive rate (TPR) of 71.4% and a false positive rate (FPR) of just 7.4%. It is important to note that this low FPR ensures that the model remains profitable, as the cost of false positives is contained. The ensemble achieved a best profit of 265.4, confirming its superiority in aligning prediction with economic utility.

Figure 3 – Confusion Matrix

True Label	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

Predicted Label

True Label	Predicted 0	Predicted 1
Actual 0	2296	184
Actual 1	2	5

Predicted Label

In comparison with single-model applications, the ensemble method yielded a more favourable trade-off between recall and profitability. For instance, although Gradient Boosting achieved a perfect recall (TPR = 1.0), its high FPR (27.1%) resulted in a substantial financial loss (-1294.7). In a similar manner, AdaBoost attained a relatively high TPR (57.1%) but exhibited an FPR of 10.9%, resulting in a negative profit of (-289.5). Conversely, tree-based models such as ExtraTrees and RandomForest exhibited a more conservative performance, with lower TPRs of 42.9% and 14.3%, respectively. These models also maintained FPRs below 3%, resulting in modest yet positive profits.

Table 4 – Base Learner Performances

Model:	TPR	FPR
ExtraTrees	0.429	0.023
XGBoost	0.143	0.000
RandomForest	0.143	0.001
AdaBoost	0.571	0.110
GradientBoosting	1.000	0.271
Profit-driven Ensemble	0.714	0.074

The ensemble approach effectively combines the strengths of these individual models, leveraging their complementary patterns while maintaining economic viability. Its higher recall demonstrates improved ability to identify true acquisition targets, a key advantage in the M&A context. Moreover, the relatively low FPR ensures that misclassifications do not erode financial gains, thereby validating the use of a profit-oriented objective in model selection and threshold optimization.

4.2 Model Robustness via Bootstrapping

To assess the robustness and generalizability of the model, a bootstrap procedure was conducted, resampling the dataset with replacement to simulate repeated model applications across varying train-test splits. This model evaluation is in line with the one of previous study (Hajek & Henriques, 2024). The distribution of ROC AUC scores across these simulations (Appendix A8, Figure 8) confirms the model’s strong and consistent predictive capability. The original AUC of 0.864 is well within the dense region of the distribution, indicating stability across different data partitions. The 95% confidence interval, ranging from 0.677 to 0.962, further demonstrates that even under less favorable sampling conditions, the model generally retains acceptable to high discriminative power.

The concentration of AUC values in the upper range of the distribution reinforces the model's robustness. While a few outliers indicate lower performance in some bootstrap samples, these are limited and do not substantially affect the overall interpretation. This suggests that the ensemble model is not overly sensitive to the composition of the training data, and its generalization error is well controlled. These findings support the reliability of the proposed approach in practical M&A target screening scenarios, where variations in available data are to be expected.

4.3 Statistical Significance of Features via Bootstrapping Stability Analysis

In order to evaluate the statistical robustness of each input variable in the model, the bootstrapping method was employed to calculate the distribution of feature importances across 1,000 model replications. This approach (Katsafados, Leledakis, Pyrgiotakis, Androutsopoulos, & Fergadiotis, 2023) tests significance by evaluating whether a feature consistently contributes to the model across different random samples of the data. It can be deduced that if a feature exhibits high mean importance and low variance across bootstraps, it is likely to have a stable and generalizable effect.

The findings indicate that Size_1 (log Revenue), Profitability_5 (Return on Assets), and Growth_1 (3-year Revenue CAGR) emerge as the most significant predictors (Table 5). For instance, Size_1 has an average importance of 0.112 (Std = 0.066), while Profitability_5 and Growth_1 exhibit mean importances of 0.084 and 0.055, respectively, each with relatively moderate dispersion. These values indicate that these features contribute substantially to the model's predictive capacity across resamples.

4.3.1 The Importance of Text-based Information

The ten features labeled BD1 through BD10 represent the dimensions of a reduced embedding space derived from FinBERT. While individual BDi features exhibit moderate importance values (BD4: 0.133, BD3: 0.049), it is critical to interpret them as components of a unified textual representation rather than as standalone economic variables. Given that embeddings are inherently distributed representations, the interpretability and significance of any one BDi component are limited. However, viewed as a group, the BDi dimensions collectively contribute a meaningful portion of the total importance, suggesting that textual sentiment and tone captured by FinBERT have predictive value. Thus, while individual BD components may not outperform core accounting features, the group as a whole should be regarded as statistically and economically relevant.

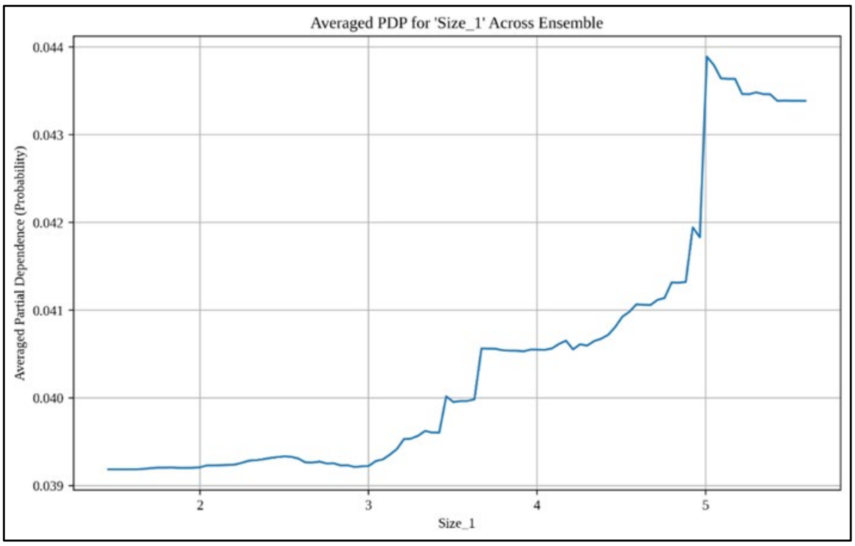
Table 5 – Feature Importance Across Bootstrap

	count	mean	std	min	25%	50%	75%	max
Size_1	**1000**	**0.1124**	**0.0663**	**0.0286**	**0.0574**	**0.0788**	**0.1816**	**0.3474**
Size_2	1000	0.06349	0.02723	0.02714	0.04777	0.05915	0.07061	0.25159
Capital_Structure_3	1000	0.03937	0.0125	0.01441	0.03091	0.03749	0.04613	0.13594
Efficiency_1	1000	0.04091	0.01067	0.02012	0.03372	0.03924	0.04539	0.09828
Profitability_3	1000	0.05283	0.01892	0.02334	0.04067	0.04902	0.06102	0.23658
Capital_Structure_2	1000	0.03522	0.01132	0.01704	0.02823	0.03277	0.03881	0.11867
Liquidity_3	1000	0.04436	0.01331	0.01987	0.03387	0.04233	0.05301	0.11691
Growth_1	**1000**	**0.0551**	**0.0209**	**0.0217**	**0.042**	**0.0527**	**0.0635**	**0.2113**
Profitability_5	**1000**	**0.0841**	**0.0466**	**0.026**	**0.054**	**0.0688**	**0.0916**	**0.3185**
Profitability_2	1000	0.03975	0.01447	0.01847	0.03108	0.03613	0.04342	0.16282
BD1	1000	0.03586	0.01845	0.01282	0.02638	0.0318	0.03915	0.20086
BD2	1000	0.0272	0.01339	0.01026	0.02032	0.02414	0.0291	0.15891
BD3	1000	0.04861	0.03298	0.01473	0.03028	0.03974	0.05273	0.21466
BD4	1000	0.13372	0.06528	0.02491	0.08172	0.10097	0.20266	0.26058
BD5	1000	0.03642	0.01367	0.01486	0.02664	0.03222	0.04421	0.10341
BD6	1000	0.02973	0.01675	0.01126	0.02169	0.02617	0.03315	0.19774
BD7	1000	0.02998	0.01246	0.01069	0.02209	0.02632	0.03349	0.10121
BD8	1000	0.03328	0.01232	0.01338	0.02614	0.03122	0.03706	0.1656
BD9	1000	0.02852	0.01328	0.01011	0.02162	0.02561	0.03099	0.16211
BD10	1000	0.02923	0.01001	0.01272	0.02246	0.027	0.03377	0.1133

4.3.2 Partial Dependence Plots Analysis

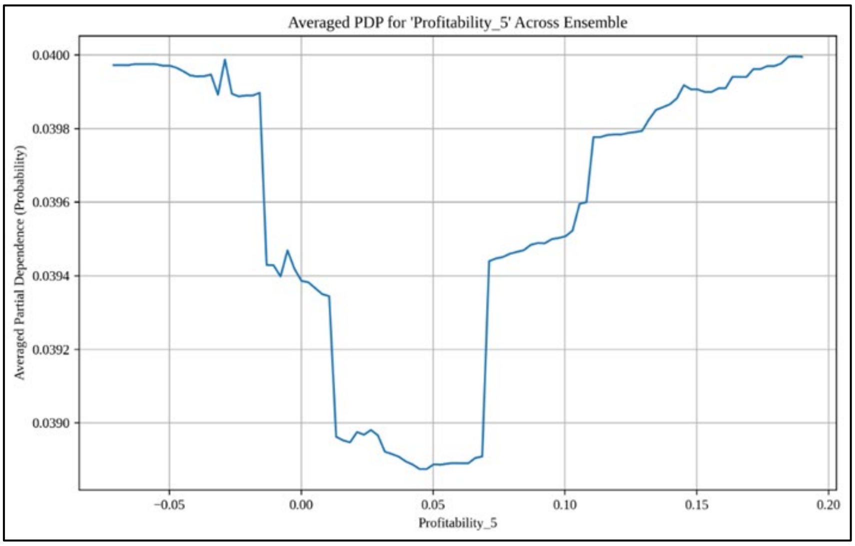
To better understand how each of the most robust predictors individually influences the model's predictions, Partial Dependence Plot (PDP) Analysis for Size_1, Profitability_5, and Growth_1 was employed. PDPs visualize the marginal effect of a single feature on the predicted probability by averaging the model's output over the entire dataset while varying that feature alone. This helps isolate and interpret the specific relationship between each variable and the model's prediction, independent of the influence of other features. In this study, PDPs serve to (i) confirm the directionality and functional form of the relationships learned by the model, (ii) reveal non-linear effects (iii) validate the predictive robustness of the features identified via bootstrap resampling, and (iv) enhance model transparency for communication. The clean and interpretable shapes of the PDPs support the conclusion that Size_1, Profitability_5, and Growth_1 are not only statistically robust but also economically meaningful predictors of M&A target likelihood.

Figure 4 – Partial Dependence Plots of the Most Significant Features (Size_1)



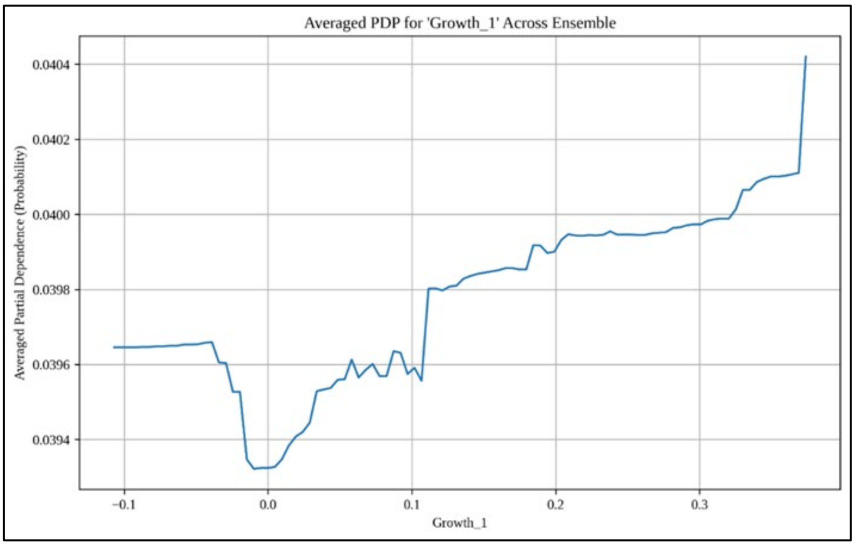
The PDP for Size_1 exhibits a clear monotonic increase, particularly accelerating after log(Revenue) exceeds 4.5. This suggests a strong positive association between firm size and predicted probability, likely reflecting the model's belief that larger firms are more likely to be selected as M&A targets. This may be due to larger firms offering greater strategic value, stronger operational capabilities, or more stable financial profiles, all of which can increase their attractiveness in acquisition scenarios. The smooth and upward trend indicates a stable and interpretable relationship with minimal noise.

Figure 5 – Partial Dependence Plots of the Most Significant Features (Profitability_5)



The relationship between Profitability_5 and predicted probability is non-monotonic and U-shaped. The lowest probabilities occur around moderate ROA values (~0.03–0.06), with elevated probabilities both at low (possibly distressed) and high (high-performing) ends. This may suggest that the model captures non-linear dynamics where extreme financial positions, either strong performance or high risk, are more predictive of the Target class than average outcomes.

Figure 6 – Partial Dependence Plots of the Most Significant Features (Growth_1)



The PDP for Growth_1 shows a generally increasing trend, with a local minimum around zero and sharp increase for CAGR values above 0.3. This confirms that strong revenue growth is positively associated with the outcome, and implies the model uses recent firm momentum as a meaningful predictor. The consistent upward shape enhances its interpretability and supports its statistical robustness.

4.4 Case study – CTT acquisition of Cacesa

To transition from the broader applicability of the model to the specific case that originally motivated this study, a retrospective assessment was made of whether the acquisition of Cacesa could have been anticipated using the machine learning approach that had been developed. In the test year, the model identified 189 potential acquisition targets. The primary objective of this study was to implement machine learning techniques to support the identification of M&A targets in a real-world setting. It is evident that identifying a single acquisition can be a challenging task, analogous to the process of finding a needle in a haystack. Consequently, the model's capacity to generate a concise shortlist of plausible candidates is of significant value in the context of strategic decision-making.

In the context of the CTT case, geographical relevance was key. Anticipating an Iberian acquisition, a geographic filter was applied after model prediction, reducing the list of potential targets from 189 to 17 firms based in Spain and Portugal (Table 5). Among these, Cacesa was distinguished by its elevated predicted probability, which was among the most significant values calculated by the model. It is noteworthy that Cacesa attained fourth position overall among Iberian candidates and achieved the highest predicted score within its relevant industry segment, which is defined as Courier, Postal, Air Freight, and Land-based Logistics.

Table 6 – Iberian Targets

Company Common Name	TRBC Industry Name	Country of Headquarters	Predicted Probability	Rank
Food Orchestrator SA	Courier, Postal, Air Freight & Land-based Logistics	Portugal	0.088050744	6
Goi Travel SL	Ground Freight & Logistics	Spain	0.07490281	8
Trans Sev SL	Ground Freight & Logistics	Spain	0.067712043	15
Compania Auxiliar al Cargo Express SA	**Courier, Postal, Air Freight & Land-based Logistics**	**Spain**	**0.090095312**	**4**
Transportes Aragoneses SA	Ground Freight & Logistics	Spain	0.087523876	7
Silos Metalicos Zaragoza SLU	Ground Freight & Logistics	Spain	0.098123466	3
Anymore Transport SL	Ground Freight & Logistics	Spain	0.068108383	13
Seur SA	Ground Freight & Logistics	Spain	0.08822484	5
San Jose Lopez SA	Ground Freight & Logistics	Spain	0.12425095	2
Empresa Naviera Elcano SA	Marine Freight & Logistics	Spain	0.068143225	12
Primafrio SL	Courier, Postal, Air Freight & Land-based Logistics	Spain	0.072509395	9
Montfrisa SA	Ground Freight & Logistics	Spain	0.069336616	11
Transportes el Mosca SA	Ground Freight & Logistics	Spain	0.067956663	14
Fred Olsen SA	Marine Freight & Logistics	Spain	0.07133689	10
Trans X Tar SL	Ground Freight & Logistics	Spain	0.067690891	17
Vicarli SA	Ground Freight & Logistics	Spain	0.067700707	16
Metratir Automoviles SL	Ground Freight & Logistics	Spain	0.187633608	1

5 Conclusions

The central question guiding this study was whether machine learning models can effectively predict M&A targets. Drawing upon the acquisition of Cacesa by CTT as a pertinent case study, the findings underscore the efficacy of machine learning techniques, particularly those trained on both financial and textual attributes, in substantially enhancing the model's discriminative capacity for identifying potential acquisition candidates. These results serve to reinforce the reliability of such models and highlight their practical relevance in the context of M&A screening processes.

A key methodological component of this work is the application of a profit-oriented evaluation framework, previously established in the literature (Hajek & Henriques, 2024), and particularly suitable for reflecting the trade-offs practitioners face in real-world M&A scenarios. Its implementation is crucial for aligning model evaluation with economic decision-making by emphasizing the financial utility of correct predictions alongside traditional accuracy metrics.

Nonetheless, the study acknowledges certain limitations, most notably the restricted availability and depth of financial and narrative data for private firms, which represent a significant portion of the Logistics sector. Future research should therefore aim to incorporate richer narrative sources, such as detailed company filings, press releases, and sentiment-informed news coverage, to expand the feature set and improve predictive performance.

The overall ambition of this research was to implement machine learning models in the context of target selection in M&A, with a focus on realism and industry-specific relevance. The model was subjected to retrospective testing. Although perfect precision was not expected or achieved, the implementation of a systematic, data-driven screening methodology represents a significant advancement towards practical deployment. In the specific context of the CTT case, the outcome provides concrete evidence of the model's relevance and applicability in real-world scenarios.

More broadly, the findings underscore the potential of machine learning to enhance Equity Research workflows by supporting forward-looking assessments of M&A optionality. The integration of predictive modelling, particularly for firms pursuing acquisition strategies, enables the proactive detection of likely acquisition candidates. Consequently, the study provides practical value for analysts and industry professionals seeking to enhance the analytical depth and strategic precision of their M&A evaluation frameworks.

Appendix A provides additional clarification on the methodology, including the relevant Python code and supplementary results.

Appendix B expands on CTT’s valuation and details its M&A activity during 2024.

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7 Appendix A: Supplementary Materials for M&A Target Selection Model

Appendix A1: Python Code 1 – FinBERT (NLP) Application

```
#FinBERT Application
!pip install transformers xgboost pandas scikit-learn tqdm --quiet
from transformers import AutoTokenizer, AutoModel
import torch
from tqdm import tqdm

model_name = "yiyanghkust/finbert-tone"
tokenizer = AutoTokenizer.from_pretrained(model_name)
model = AutoModel.from_pretrained(model_name).eval().to("cuda" if torch.cuda.is_available() else "cpu")

def embed_batch(texts, batch_size=32):
    device = "cuda" if torch.cuda.is_available() else "cpu"
    embeddings = []
    for i in tqdm(range(0, len(texts), batch_size)):
        batch = texts[i:i+batch_size]
        tokens = tokenizer(batch, padding=True, truncation=True, return_tensors='pt', max_length=128)
        tokens = {k: v.to(device) for k, v in tokens.items()}
        with torch.no_grad():
            output = model(**tokens)
        batch_embeddings = output.last_hidden_state.mean(dim=1).cpu()
        embeddings.append(batch_embeddings)
    return torch.cat(embeddings).numpy()

def get_embedding(text):
    inputs = tokenizer(text, return_tensors="pt", truncation=True, padding=True)
    with torch.no_grad():
        outputs = model(**inputs)
    return outputs.last_hidden_state[:, 0, :].squeeze().numpy()

descriptions = df['Business Description'].fillna("").tolist()
bert_embeddings = np.vstack([get_embedding(desc) for desc in descriptions])
```

Appendix A2: Python Code 2 – UMAP Application

```
!pip install umap-learn
import umap

df['bert_embeddings'] = [vec for vec in bert_embeddings]
embedding_matrix = np.vstack(df['bert_embeddings'].values)

reducer = umap.UMAP(
    n_neighbors=15,
    n_components=10,
    random_state=42,
    metric='cosine'
)

embedding_umap = reducer.fit_transform(embedding_matrix)

for i in range(embedding_umap.shape[1]):
    df[f'umap_{i+1}'] = embedding_umap[:, i]
```

The first two code snippets demonstrate the application of an NLP algorithm that converts the Business and Product Descriptions into 768-dimensional numerical vectors. These vectors are then reduced to 10 dimensions using UMAP. The resulting UMAP features were subsequently added manually to the final

A3: Python Code 3 – Data Preparation

```
!pip install imbalanced-learn
!pip install skrebate
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import re
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.metrics import classification_report, roc_auc_score, precision_recall_curve, auc, f1_score, confusion_matrix,
accuracy_score
from sklearn.metrics import roc_curve
from sklearn.preprocessing import RobustScaler
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier, AdaBoostClassifier, GradientBoostingClassifier
from sklearn.utils import resample
from sklearn.feature_selection import mutual_info_classif, chi2
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import BorderlineSMOTE
from imblearn.under_sampling import CondensedNearestNeighbour
from imblearn.pipeline import Pipeline

file_path = "privatecompaniesfinbert.xlsx"
df = pd.read_excel(file_path)
```

```
fiscal_years = [f"FY-{i}" if i > 0 else "FY0" for i in reversed(range(10))]

feature_mapping = {
    "Size_1": "Revenue", "Size_2": "Total Assets", "Profitability_1": "EBIT Margin", "Profitability_2": "EBITDA Margin",
    "Profitability_3": "Net Income Margin", "Profitability_4": "ROCE", "Profitability_5": "ROA", "Efficiency_1": "Asset Turnover",
    "Efficiency_2": "Working Capital to Sales", "Liquidity_1": "Current Ratio", "Liquidity_2": "Quick Ratio",
    "Liquidity_3": "Cash Ratio", "Capital_Structure_1": "Debt to Equity", "Capital_Structure_2": "Debt to Assets",
    "Capital_Structure_3": "Long Term Debt to Capital", "Growth_1": "Revenue CAGR 3yrs", "Growth_2": "EBIT CAGR 3yrs",
    "BD1": "umap_1", "BD2": "umap_2", "BD3": "umap_3", "BD4": "umap_4", "BD5": "umap_5",
    "BD6": "umap_6", "BD7": "umap_7", "BD8": "umap_8", "BD9": "umap_9", "BD10": "umap_10"
}

# Reshape data to long format for simplicity
records = []
for idx, row in df.iterrows():
    for fy in fiscal_years:
        record = {
            "Company": row.get("Company Common Name", None),
            "Year": fy
        }
        for new_col, base in feature_mapping.items():
            full_col = f"{base} {fy}"
            record[new_col] = row.get(full_col, None)
        # Target column
        deal_flag_col = f"Deal Flag {fy}"
        target_val = str(row.get(deal_flag_col, "")).strip().lower()
        record["Target"] = 1 if target_val == "target" else 0

        records.append(record)

long_df = pd.DataFrame(records)

features = list(feature_mapping.keys())
```

Appendix A4: Python Code 4 – Feature Engineering

```
# Filter for rows where Target == 1 and at least one feature is missing
target_1_missing = long_df[(long_df["Target"] == 1) & (long_df[features].isnull().any(axis=1))].copy()
target_1_missing = target_1_missing.copy()
# Function to replace missing values with prior years data
def fill_with_prior_year(row, feature):
    company = row['Company']
    current_year_index = fiscal_years.index(row['Year'])
    for year_offset in range(1, min(current_year_index + 1, 10)):
        prior_year = fiscal_years[current_year_index - year_offset]
        prior_year_data = long_df[(long_df['Company'] == company) & (long_df['Year'] == prior_year)]
        if not prior_year_data.empty:
            prior_year_value = prior_year_data[feature].values[0]
            if pd.notna(prior_year_value):
                return prior_year_value
    return np.nan
for feature in features:
    target_1_missing[feature] = target_1_missing.apply(fill_with_prior_year, axis=1, args=(feature,))

long_df_clean = pd.concat([long_df[(long_df['Target'] == 0) | (long_df[features].notna().all(axis=1))], target_1_missing])

# Again Filter for rows where Target == 1 and at least one feature is missing
target_1_few_missing = long_df[(long_df['Target'] == 1) & (long_df[features].isnull().any(axis=1))].copy()
numeric_df = long_df[features].apply(pd.to_numeric, errors='coerce')
# Replace missing values with median
feature_medians = numeric_df.median()
target_1_few_missing[features] = (
    target_1_few_missing[features]
    .fillna(feature_medians)
    .infer_objects(copy=False)
)

fully_valid_rows = long_df[long_df[features].notna().all(axis=1)]
long_df_clean = pd.concat([fully_valid_rows, target_1_few_missing], ignore_index=True)
target_1_missing = long_df[(long_df['Target'] == 1) & (long_df[features].isnull().any(axis=1))]

# Drop any remaining row with missing feature
long_df_clean = long_df.dropna(subset=features)
```

To ensure maximum availability and reliability of the Target companies, which were already limited in number, missing values were first imputed using previously known values. If unavailable, the median value was used, but only for Targets with a single missing variable. Any remaining Targets or Non-Targets with missing values were subsequently excluded from the dataset.

Appendix A5: Python Code 5 – Train/Test Split

```
# Split data into training and testing sets
train_df = long_df_clean[long_df_clean["Year"].isin([f"FY-{i}" for i in range(2, 10) if i != 3])]
test_df = long_df_clean[long_df_clean["Year"] == "FY0"]

features = [col for col in long_df_clean.columns if col not in ["Year", "Target", "Company"]]
target = "Target"

X_train = train_df[features].astype(float)
y_train = train_df[target]

X_test = test_df[features].astype(float)
y_test = test_df[target]

X = long_df_clean[features].astype(float)
y = long_df_clean["Target"]
```

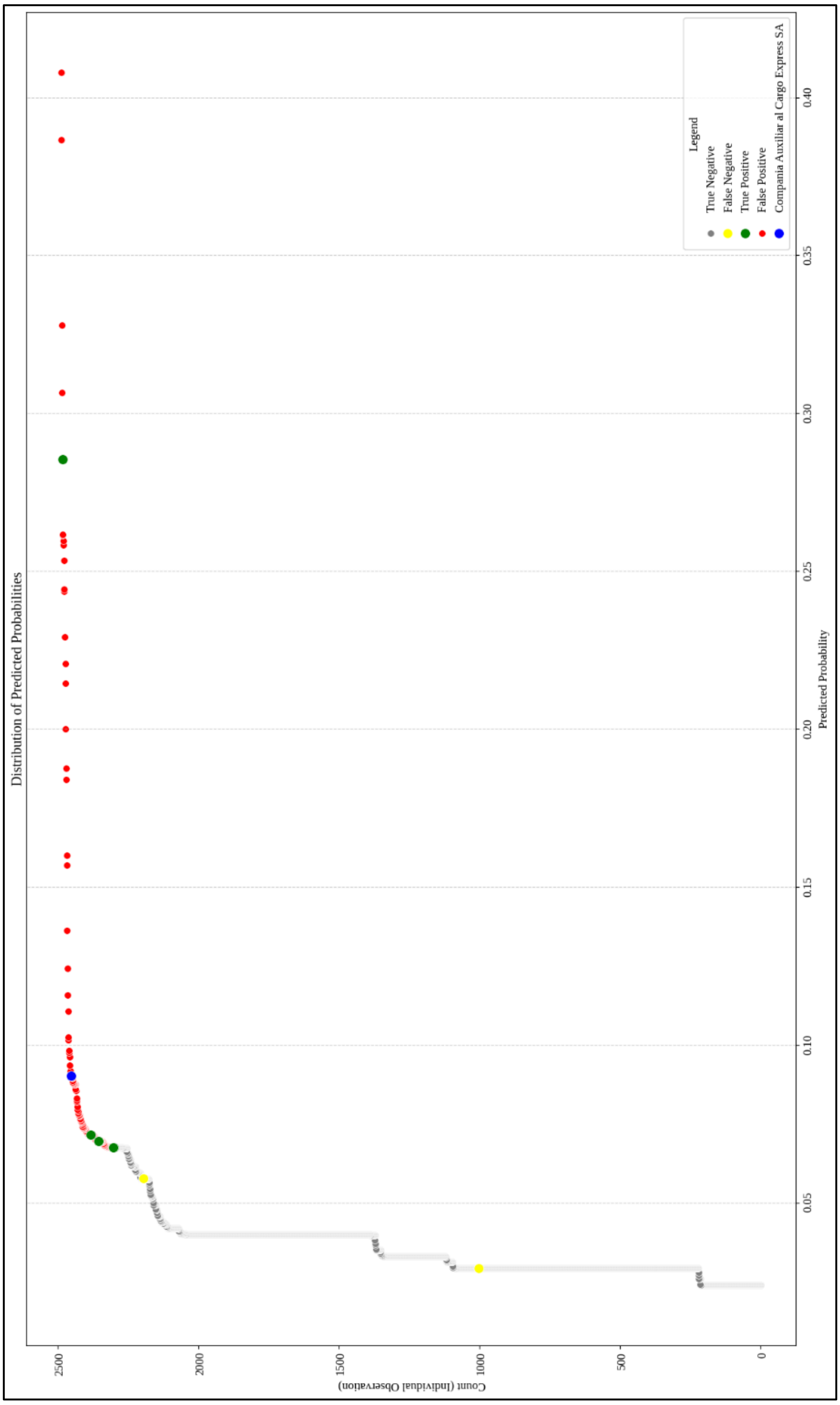
Appendix A6: Python Code 6 – Feature Selection & Profit-driven Ensemble

```
# Chi-Squared
# Ensure non-negative values for chi2
X_train_chi2 = X_train_fs.copy()
potentially_negative_features = [col for col in X_train_chi2.columns if (X_train_chi2[col] < 0).any()]
if potentially_negative_features:
    print{potentially_negative_features}
    X_train_chi2[potentially_negative_features] = X_train_chi2[potentially_negative_features] -
X_train_chi2[potentially_negative_features].min().min()
chi2_scores, chi2_pvalues = chi2(X_train_chi2, y_train_fs)
chi2_results = pd.DataFrame({'Feature': X_train_fs.columns, 'Chi2 Score': chi2_scores, 'Chi2 P-value':
chi2_pvalues})
chi2_results = chi2_results.sort_values(by='Chi2 Score', ascending=False).reset_index(drop=True)

# ReliefF
# Ensure finite values for ReliefF
from skrebate import ReliefF
fs = ReliefF(n_neighbors=10)
if np.isfinite(X_train.values).all():
   fs.fit(X_train.values, y_train.values)
   relief_scores = fs.feature_importances_
   relief_results = pd.DataFrame({'Feature': X_train.columns, 'ReliefF Score': relief_scores})
   relief_results = relief_results.sort_values(by='ReliefF Score', ascending=False).reset_index(drop=True)
   else:
      relief_results = None

# Gain Ratio with Discretization
def entropy(target_col):
    elements, counts = np.unique(target_col, return_counts=True)
    entropy = np.sum([(-counts[i] / np.sum(counts)) * np.log2(counts[i] / np.sum(counts))
                      for i in range(len(elements))])
    return entropy

def info_gain(data, feature_name, target_name="Target"):
    total_entropy = entropy(data[target_name])
    values, counts = np.unique(data[feature_name], return_counts=True)
    weighted_entropy = np.sum([(counts[i] / np.sum(counts)) * entropy(data.loc[data[feature_name] == values[i],
target_name])
    for i in range(len(values))])
        information_gain = total_entropy - weighted_entropy
    return information_gain

def split_information(data, feature_name):
    values, counts = np.unique(data[feature_name], return_counts=True)
    proportions = counts / np.sum(counts)
    split_info = -np.sum([p * np.log2(p) for p in proportions if p > 0])
    return split_info

n_bins = 10

X_train_discretized = X_train_fs.copy()

continuous_features = X_train_fs.select_dtypes(include=np.number).columns.tolist()

for feature in continuous_features:
    if X_train_discretized[feature].nunique() <= 1:
        continue
    try:
        X_train_discretized[f'{feature}_discrete'], bins = pd.qcut(
            X_train_discretized[feature],
            q=n_bins,
            labels=False,
            duplicates='drop',
            retbins=True
        )
        X_train_discretized[f'{feature}_discrete'] = X_train_discretized[f'{feature}_discrete'].astype(str)

    except Exception as e:
        try:
             X_train_discretized[f'{feature}_discrete'] = pd.cut(
                 X_train_discretized[feature],
                 bins=n_bins,
                 labels=False,
                 include_lowest=True
             ).astype(str)
        except Exception as e_cut:
            X_train_discretized[f'{feature}_discrete'] = X_train_discretized[feature].astype(str)

df_gain_ratio = X_train_discretized.copy()
df_gain_ratio['Target'] = y_train_fs.values

gain_ratio_results = []
for feature in continuous_features:
    discrete_feature_name = f'{feature}_discrete'
    if discrete_feature_name in df_gain_ratio.columns:
        ig = info_gain(df_gain_ratio, discrete_feature_name, target_name="Target")
        split_info = split_information(df_gain_ratio, discrete_feature_name)
        if split_info > 1e-6:
             gain_ratio = ig / split_info
        else:
             gain_ratio = 0

        gain_ratio_results.append({'Feature': feature, 'Gain Ratio': gain_ratio})

gain_ratio_df = pd.DataFrame(gain_ratio_results)
gain_ratio_df = gain_ratio_df.sort_values(by='Gain Ratio', ascending=False).reset_index(drop=True)
```

```python
# Normalize Relevance Scores [0, 1]

# Normalize Information Gain
if 'ig_results' in locals() and ig_results is not None and not ig_results.empty:
    scaler = MinMaxScaler()
    ig_results['IG_Normalized'] = scaler.fit_transform(ig_results[['Information Gain']])
else:
    ig_results = pd.DataFrame(columns=['Feature', 'IG_Normalized'])

# Normalize Chi-Squared Scores
if 'chi2_results' in locals() and chi2_results is not None and not chi2_results.empty:
    scaler = MinMaxScaler()
    chi2_results['Chi2 Score_Clean'] = chi2_results['Chi2 Score'].fillna(0)
    chi2_results['Chi2_Normalized'] = scaler.fit_transform(chi2_results[['Chi2 Score_Clean']])
else:
    chi2_results = pd.DataFrame(columns=['Feature', 'Chi2_Normalized'])

# Normalize ReliefF Scores
if 'relief_results' in locals() and relief_results is not None and not relief_results.empty:
    scaler = MinMaxScaler()
    relief_results['ReliefF_Normalized'] = scaler.fit_transform(relief_results[['ReliefF Score']])
else:
    relief_results = pd.DataFrame(columns=['Feature', 'ReliefF_Normalized'])

# Normalize Gain Ratio
if 'gain_ratio_df' in locals() and gain_ratio_df is not None and not gain_ratio_df.empty:
    scaler = MinMaxScaler()
    gain_ratio_df['Gain Ratio_Clean'] = gain_ratio_df['Gain Ratio'].fillna(0)
    gain_ratio_df['GainRatio_Normalized'] = scaler.fit_transform(gain_ratio_df[['Gain Ratio_Clean']])
else:
    gain_ratio_df = pd.DataFrame(columns=['Feature', 'GainRatio_Normalized'])

# Aggregate Normalized Scores

if not ig_results.empty:
    aggregated_scores = ig_results[['Feature', 'IG_Normalized']].copy()
    aggregated_scores = aggregated_scores.set_index('Feature')
else:
    print("No Information Gain results to start aggregation.")
    aggregated_scores = pd.DataFrame(index=features)
    aggregated_scores['IG_Normalized'] = np.nan

if not chi2_results.empty:
     aggregated_scores = aggregated_scores.merge(chi2_results[['Feature', 'Chi2_Normalized']].set_index('Feature'),
                                             left_index=True, right_index=True, how='left')
if not relief_results.empty:
     aggregated_scores = aggregated_scores.merge(relief_results[['Feature',
'ReliefF_Normalized']].set_index('Feature'),
                                             left_index=True, right_index=True, how='left')
if not gain_ratio_df.empty:
     aggregated_scores = aggregated_scores.merge(gain_ratio_df[['Feature',
'GainRatio_Normalized']].set_index('Feature'),
                                             left_index=True, right_index=True, how='left')


# Calculate the average score for each feature across available methods
aggregated_scores['Average Score'] = aggregated_scores.mean(axis=1)
aggregated_scores = aggregated_scores.reset_index()
aggregated_scores = aggregated_scores.rename(columns={'index': 'Feature'})
ranked_features = aggregated_scores.sort_values(by='Average Score', ascending=False).reset_index(drop=True)

# Feature Elimination based on Aggregated Score
top_n_aggregated = 20
final_selected_features_aggregated = ranked_features['Feature'].head(top_n_aggregated).tolist()

# Training Models with Aggregated Selected Features
if 'X_train' in locals() and 'X_test' in locals():
    X_train_selected_agg = X_train[final_selected_features_aggregated].astype(float)
    X_test_selected_agg = X_test[final_selected_features_aggregated].astype(float)
    # Apply SMOTE and CNN to the aggregated selected features
    smote = BorderlineSMOTE(random_state=42, kind='borderline-2', k_neighbors=5)
    under = CondensedNearestNeighbour(random_state=42)
    pipeline = Pipeline(steps=[('o', smote), ('u', under)])
    X_res_selected_agg, y_res_agg = pipeline.fit_resample(X_train_selected_agg, y_train)
    models_agg = {
        "ExtraTrees": ExtraTreesClassifier(n_estimators=100, random_state=42),
        "RandomForest": RandomForestClassifier(n_estimators=10, random_state=42),
        "AdaBoost": AdaBoostClassifier(n_estimators=5, random_state=42),
        "GradientBoosting": GradientBoostingClassifier(n_estimators=100, random_state=42),
        "XGBoost": XGBClassifier(eval_metric='logloss', random_state=42)
    }
    results_selected_agg = []
    # Set benefit/cost parameters for profit-driven evaluation
    b0 = 500000.0
    c1 = 10000.0
    for name, model in models_agg.items():
        model.fit(X_res_selected_agg, y_res_agg)
        probas = model.predict_proba(X_test_selected_agg)[:, 1]
        if len(np.unique(y_test)) < 2 or len(np.unique(probas)) < 2:
            continue
        fpr, tpr, thresholds = roc_curve(y_test, probas)
        pi_0 = np.mean(y_test == 1)  # P(target)
        pi_1 = 1 - pi_0        # P(non-target)
        profits = pi_0 * tpr * b0 - pi_1 * fpr * c1
        results_selected_agg.append({
            'Model': name,
            'Best Threshold': best_threshold,
            'Best Profit': best_profit,
            'TPR': tpr[best_idx],
            'FPR': fpr[best_idx]
        })

    y_prob_rf_selected_agg = models_agg['RandomForest'].predict_proba(X_test_selected_agg)[:, 1]
    y_prob_et_selected_agg = models_agg['ExtraTrees'].predict_proba(X_test_selected_agg)[:, 1]
    y_prob_ab_selected_agg = models_agg['AdaBoost'].predict_proba(X_test_selected_agg)[:, 1]
    y_prob_gb_selected_agg = models_agg['GradientBoosting'].predict_proba(X_test_selected_agg)[:, 1]
    y_prob_xgb_selected_agg = models_agg['XGBoost'].predict_proba(X_test_selected_agg)[:, 1]

    # Soft-voting Ensemble Method
    y_prob_ensemble_selected_agg = (y_prob_rf_selected_agg + y_prob_et_selected_agg + y_prob_ab_selected_agg +
y_prob_gb_selected_agg + y_prob_xgb_selected_agg) / 5
    def profit_score(y_true, y_prob, b0, c1):
      fpr, tpr, thresholds = roc_curve(y_true, y_prob)
      pi_0 = np.mean(y_true == 1)
      pi_1 = np.mean(y_true == 0)
      profits = pi_0 * b0 * tpr - pi_1 * c1 * fpr
      best_idx = np.argmax(profits)
      return {
        "best_threshold": thresholds[best_idx],
        "best_profit": profits[best_idx],
        "tpr": tpr[best_idx],
        "fpr": fpr[best_idx],
        "all_profits": profits,
        "all_thresholds": thresholds
      }

    result_ensemble_selected_agg = profit_score(y_test, y_prob_ensemble_selected_agg, b0, c1)
    best_threshold_selected_agg = result_ensemble_selected_agg['best_threshold']
    y_pred_ensemble_selected_agg = (y_prob_ensemble_selected_agg >= best_threshold_selected_agg).astype(int)
    conf_matrix_selected_agg = confusion_matrix(y_test, y_pred_ensemble_selected_agg)
else:
    print("\nX_train or X_test not found. Cannot re-train models with aggregated selected features.")
```

Appendix A7 – Model Predictions

Figure 7 – Model Predictions

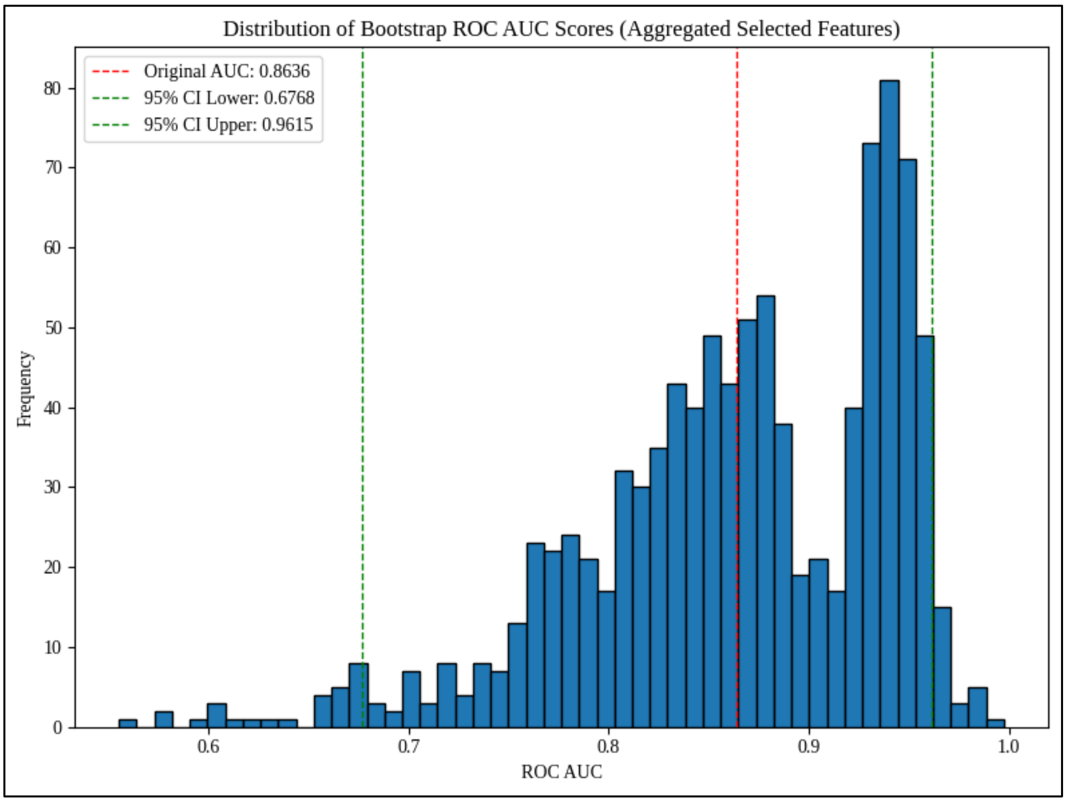


Appendix A7 illustrates the model's predictive performance, particularly its ability to accurately rank observations by their likelihood of being a target. Most True Positives are concentrated in the first decile of predicted probabilities, supporting the model's strong ranking capability, as reflected by an ROC AUC of 0.864. Notably, Cacesa (in blue) stands out as one of the companies with the highest predicted scores. While the presence of False Positives (in red) was expected, their number is relatively limited (only 184) thanks to the model's ranking strength. This controlled level of misclassification contributes to a net positive return within the profit-driven framework.

Appendix A8: Python Code 7 – Bootstrapping Technique for Model Robustness Test

```
# Bootstrap ROC AUC - Testing Model Robustness
n_bootstraps_auc_agg_selected = 1000
auc_scores_agg_selected = []

if 'X_test_selected_agg' in locals() and X_test_selected_agg is not None and 'y_test' in locals() and y_test is not None:
    test_data_agg_selected = pd.concat([X_test_selected_agg.reset_index(drop=True), y_test.reset_index(drop=True)], axis=1)
    imputer_agg_selected = SimpleImputer(strategy='median')
    if not X_test_selected_agg.empty:
      imputer_agg_selected.fit(X_test_selected_agg)
    else:
      imputer_agg_selected = None

    if imputer_agg_selected is not None and 'models_agg' in locals():
        for i in range(n_bootstraps_auc_agg_selected):
            sample_agg_selected = resample(test_data_agg_selected, replace=True, random_state=i)
            X_sample_agg_selected = sample_agg_selected[final_selected_features_aggregated]
            y_sample_agg_selected = sample_agg_selected[target]
            if len(np.unique(y_sample_agg_selected)) < 2:
                continue
            X_sample_agg_selected_imputed = imputer_agg_selected.transform(X_sample_agg_selected)
            y_prob_rf_sample_agg_selected = models_agg['RandomForest'].predict_proba(X_sample_agg_selected_imputed)[:, 1]
            y_prob_et_sample_agg_selected = models_agg['ExtraTrees'].predict_proba(X_sample_agg_selected_imputed)[:, 1]
            y_prob_ab_sample_agg_selected = models_agg['AdaBoost'].predict_proba(X_sample_agg_selected_imputed)[:, 1]
            y_prob_gb_sample_agg_selected = models_agg['GradientBoosting'].predict_proba(X_sample_agg_selected_imputed)[:, 1]
            y_prob_xgb_sample_agg_selected = models_agg['XGBoost'].predict_proba(X_sample_agg_selected_imputed)[:, 1]
            y_prob_ensemble_sample_agg_selected = (y_prob_rf_sample_agg_selected + y_prob_et_sample_agg_selected +
y_prob_ab_sample_agg_selected + y_prob_gb_sample_agg_selected + y_prob_xgb_sample_agg_selected) / 5
            try:
                auc_agg_selected = roc_auc_score(y_sample_agg_selected, y_prob_ensemble_sample_agg_selected)
                auc_scores_agg_selected.append(auc_agg_selected)
                continue
        if auc_scores_agg_selected:
            X_test_selected_agg_imputed = imputer_agg_selected.transform(X_test_selected_agg)
            y_prob_rf_orig_agg_selected = models_agg['RandomForest'].predict_proba(X_test_selected_agg_imputed)[:, 1]
            y_prob_et_orig_agg_selected = models_agg['ExtraTrees'].predict_proba(X_test_selected_agg_imputed)[:, 1]
            y_prob_ab_orig_agg_selected = models_agg['AdaBoost'].predict_proba(X_test_selected_agg_imputed)[:, 1]
            y_prob_gb_orig_agg_selected = models_agg['GradientBoosting'].predict_proba(X_test_selected_agg_imputed)[:, 1]
            y_prob_xgb_orig_agg_selected = models_agg['XGBoost'].predict_proba(X_test_selected_agg_imputed)[:, 1]
            y_prob_ensemble_orig_agg_selected = (y_prob_rf_orig_agg_selected + y_prob_et_orig_agg_selected +
y_prob_ab_orig_agg_selected + y_prob_gb_orig_agg_selected + y_prob_xgb_orig_agg_selected) / 5

            try:
                original_auc_agg_selected = roc_auc_score(y_test, y_prob_ensemble_orig_agg_selected)
            except ValueError as e:
                 original_auc_agg_selected = None

            # Calculate the confidence interval
            alpha_auc_agg_selected = 0.95
            p_lower_auc_agg_selected = ((1.0-alpha_auc_agg_selected)/2.0) * 100
            p_upper_auc_agg_selected = (alpha_auc_agg_selected+((1.0-alpha_auc_agg_selected)/2.0)) * 100
            lower_auc_agg_selected = np.percentile(auc_scores_agg_selected, p_lower_auc_agg_selected)
            upper_auc_agg_selected = np.percentile(auc_scores_agg_selected, p_upper_auc_selected)
```

Figure 8 – Model Evaluation with Bootstrapping technique



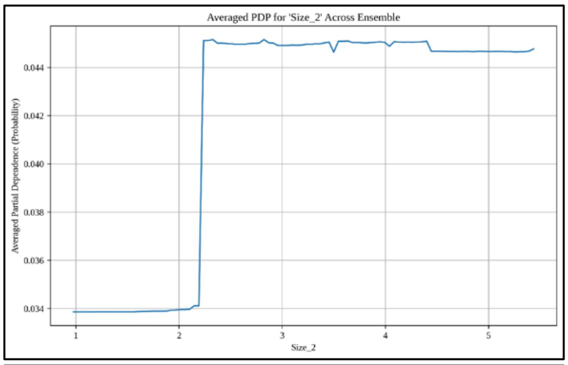
Appendix A9: Python Code 8 – PDP

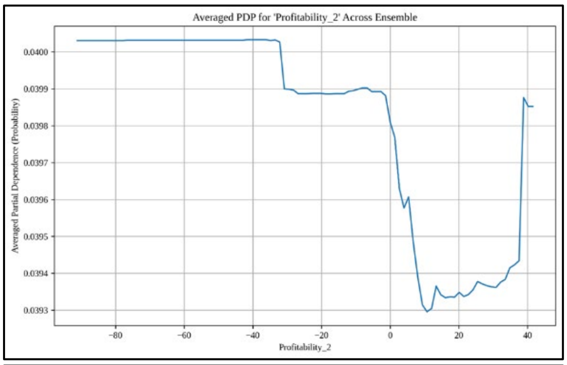
```
# Partial Dependence Plot Analysis

features_for_pdp = ['Size_1', 'Size_2', 'Capital_Structure_3', 'Efficiency_1', 'Profitability_3', 'Capital_Structure_2',
'Liquidity_3', 'Growth_1', 'Profitability_5', 'Profitability_2','BD1', 'BD2', 'BD3', 'BD4', 'BD5', 'BD6', 'BD7', 'BD8',
'BD9', 'BD10']

if 'models_agg' in locals() and 'X_test_selected_agg' in locals() and 'final_selected_features_aggregated' in locals():
    if isinstance(X_test_selected_agg, np.ndarray):
        X_test_selected_agg_df = pd.DataFrame(X_test_selected_agg, columns=final_selected_features_aggregated)
    elif isinstance(X_test_selected_agg, pd.DataFrame):
        X_test_selected_agg_df = X_test_selected_agg
    else:
        X_test_selected_agg_df = None
    if X_test_selected_agg_df is not None and not X_test_selected_agg_df.empty:
        valid_features_for_pdp = [f for f in features_for_pdp if f in final_selected_features_aggregated]
        if not valid_features_for_pdp:
            print(f"None of the specified features for PDP ({features_for_pdp}) are in the aggregated selected features
({final_selected_features_aggregated}). Cannot plot PDPs.")
        else:
            for feature_to_plot in valid_features_for_pdp:
                for name, model in models_agg.items():
                    try:
                        PartialDependenceDisplay.from_estimator(
                            estimator=model,
                            X=X_test_selected_agg_df,
                            features=[feature_to_plot],
                            method='brute',
                            kind='average',
                            response_method='predict_proba',
                        )
                        plt.suptitle(f'Partial Dependence Plot for {feature_to_plot} ({name})')
                        plt.subplots_adjust(top=0.9)
                        plt.show()
```

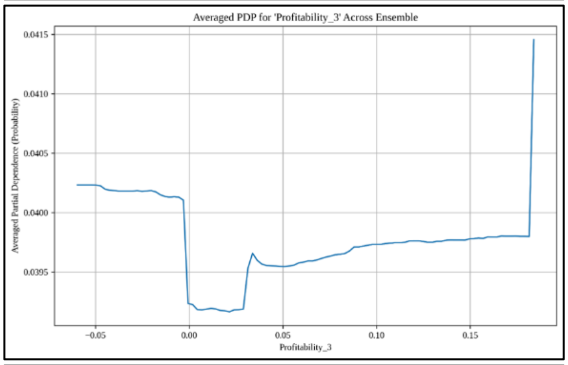
The following Python snippet illustrates the calculation of PDP for the feature Size_1 only. However, this process was repeated for each feature individually, leading to the plots in Appendix A11

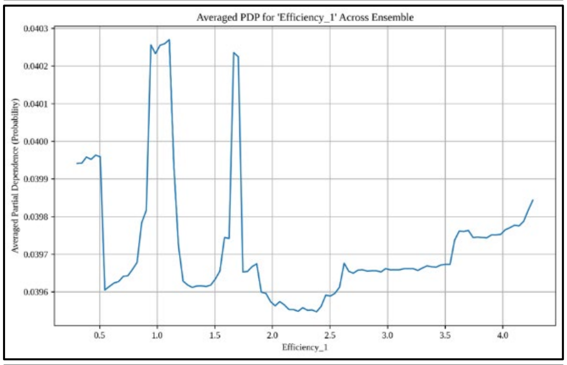
```
if isinstance(X_test_selected_agg, np.ndarray):
    X_test_selected_agg_df = pd.DataFrame(X_test_selected_agg, columns=final_selected_features_aggregated)
elif isinstance(X_test_selected_agg, pd.DataFrame):
    X_test_selected_agg_df = X_test_selected_agg
else:
    X_test_selected_agg_df = None

feature_to_average_pdp = 'Size_1'

if X_test_selected_agg_df is not None and not X_test_selected_agg_df.empty and \
   feature_to_average_pdp in X_test_selected_agg_df.columns and \
   'models_agg' in locals() and models_agg:
    first_model_name = list(models_agg.keys())[0]
    first_model = models_agg[first_model_name]
    try:
        pdp_result_first_model = PartialDependenceDisplay.from_estimator(
            estimator=first_model,
            X=X_test_selected_agg_df,
            features=[feature_to_average_pdp],
            method='brute',
            kind='average',
            response_method='predict_proba',
        )
        grid_points = pdp_result_first_model.pd_results[0].coordinates[0]
        sum_pdp_y = np.zeros(len(grid_points))
        num_models = len(models_agg)
        valid_models_for_avg = 0
        for name, model in models_agg.items():
            try:
                pdp_result = PartialDependenceDisplay.from_estimator(
                    estimator=model,
                    X=X_test_selected_agg_df,
                    features=[feature_to_average_pdp],
                    method='brute',
                    kind='average',
                    response_method='predict_proba',
                    response_coding='probability',
                )
                sum_pdp_y += pdp_result.pd_results[0].average[0]
                valid_models_for_avg += 1
                plt.close('all')
            except Exception as e:
                print(f"Could not calculate PDP for {name} for feature '{feature_to_average_pdp}': {e}")
```

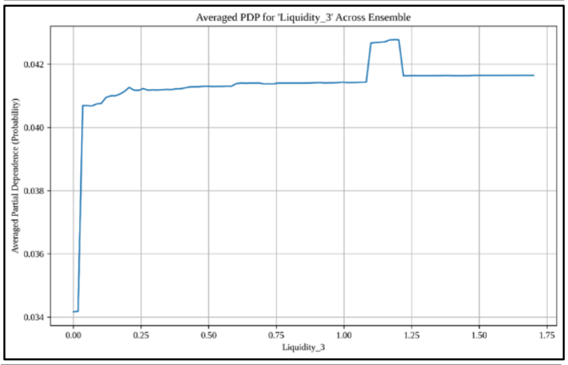
Appendix A10: Partial Dependencies Plots (other Financial Features)

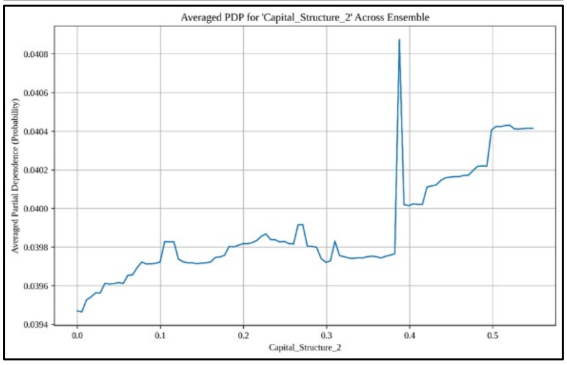


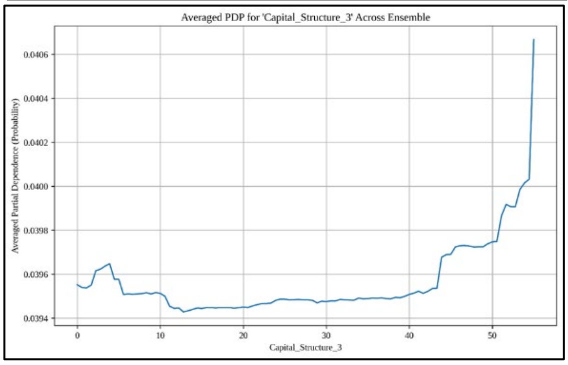












Appendix A10 presents the Partial Dependence Plots (PDPs) for financial features deemed less relevant based on the Bootstrapping Stability Analysis. These plots are provided solely as supplementary material, and no robust conclusions should be drawn from them.

Regarding text-based features, as discussed in the main body of the study, the PDPs for individual BDi variables are not particularly meaningful, as their importance should be evaluated collectively as a group rather than in isolation.

Appendix A11: Python Code 9 – Bootstrapping Stability Analysis

```
# Stability Analysis across Bootstrapped Models for Feature Significance

features_of_interest = ['Size_1', 'Size_2', 'Capital_Structure_3', 'Efficiency_1', 'Profitability_3', 'Capital_Structure_2',
'Liquidity_3', 'Growth_1', 'Profitability_5', 'Profitability_2','BD1', 'BD2', 'BD3', 'BD4', 'BD5', 'BD6', 'BD7', 'BD8', 'BD9',
'BD10']

if isinstance(X_train_selected_agg, np.ndarray):
    if len(X_train_selected_agg.shape) > 1 and len(final_selected_features_aggregated) == X_train_selected_agg.shape[1]:
        X_train_selected_agg_df = pd.DataFrame(X_train_selected_agg, columns=final_selected_features_aggregated)
    else:
        X_train_selected_agg_df = None
elif isinstance(X_train_selected_agg, pd.DataFrame):
    X_train_selected_agg_df = X_train_selected_agg
else:
    X_train_selected_agg_df = None

if X_train_selected_agg_df is not None and not X_train_selected_agg_df.empty and \
   'y_train' in locals() and y_train is not None and \
   'models_agg' in locals() and models_agg:
    n_bootstraps = 1000
    feature_importance_storage = {feature: [] for feature in features_of_interest}
    feature_rank_storage = {feature: [] for feature in features_of_interest}
    if isinstance(y_train, np.ndarray):
       y_train_series = pd.Series(y_train, index=X_train_selected_agg_df.index)
    elif isinstance(y_train, pd.Series):
        y_train_series = y_train
    else:
        y_train_series = None


    if y_train_series is not None:

        for i in range(n_bootstraps):
            bootstrap_indices = resample(X_train_selected_agg_df.index, n_samples=len(X_train_selected_agg_df), replace=True,
random_state=i)

            X_bootstrap = X_train_selected_agg_df.loc[bootstrap_indices]
            y_bootstrap = y_train_series.loc[bootstrap_indices]
            bootstrap_models = {}
            for name, original_model in models_agg.items():
                try:
                    model_clone = original_model.__class__(**original_model.get_params())
                    model_clone.fit(X_bootstrap, y_bootstrap)
                    bootstrap_models[name] = model_clone
                except Exception as e:
                    bootstrap_models[name] = None
            bootstrap_importance_df = pd.DataFrame(index=X_bootstrap.columns)
            for name, model in bootstrap_models.items():
                 if model is not None:
                     try:
                         if hasattr(model, 'feature_importances_'):
                             importance = model.feature_importances_
                             importance_series = pd.Series(importance, index=X_bootstrap.columns, name=name)
                             bootstrap_importance_df = pd.concat([bootstrap_importance_df, importance_series], axis=1)
                         else:
                             try:
                                  pfi_result = permutation_importance(
                                      model,
                                      X_bootstrap,
                                      y_bootstrap,
                                      scoring='roc_auc',
                                      n_repeats=5,
                                      random_state=i,
                                      n_jobs=-1
                                  )
                                  importance_series = pd.Series(pfi_result.importances_mean, index=X_bootstrap.columns, name=name)
                                  bootstrap_importance_df = pd.concat([bootstrap_importance_df, importance_series], axis=1)

                             except Exception as pfi_e:
                                  print(f"Failed to calculate PFI for {name} on bootstrap sample {i+1}: {pfi_e}")

                     except Exception as model_e:
                         print(f"Failed to get importance for {name} on bootstrap sample {i+1}: {model_e}")

            if not bootstrap_importance_df.empty:
                average_importance_this_bootstrap = bootstrap_importance_df.mean(axis=1)

                for feature in features_of_interest:
                    if feature in average_importance_this_bootstrap:
                        feature_importance_storage[feature].append(average_importance_this_bootstrap.loc[feature])

                ranked_features_this_bootstrap = average_importance_this_bootstrap.sort_values(ascending=False).index.tolist()

                for feature in features_of_interest:
                    if feature in ranked_features_this_bootstrap:
                        rank = ranked_features_this_bootstrap.index(feature) + 1
                        feature_rank_storage[feature].append(rank)

        importance_distribution_df = pd.DataFrame({
            feature: importances for feature, importances in feature_importance_storage.items() if importances
        })

        if not importance_distribution_df.empty:
            importance_long_df = importance_distribution_df.melt(var_name='Feature', value_name='Importance')

        else:
        rank_distribution_df = pd.DataFrame({
            feature: ranks for feature, ranks in feature_rank_storage.items() if ranks
        })

        if not rank_distribution_df.empty:
             rank_long_df = rank_distribution_df.melt(var_name='Feature', value_name='Rank')
```

CTT – Correios de Portugal SA

Hold

Medium risk

12 January 2025

Portugal

Lisbon School of Economics & Management
Universidade de Lisboa

Between Promise and Doubt: A Hold on CTT – Acquisitions at the Core of Valuation

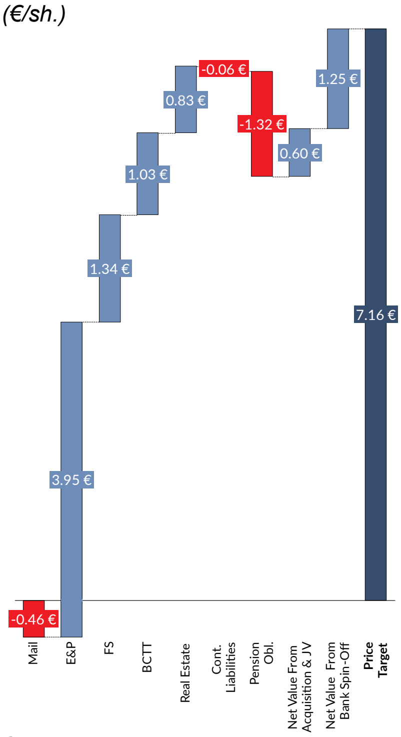
Investment Summary

Table B1: Investment Recommendation

CTT Group Equity Value	€k	€/sh.
Equity Value by Segment		
Logistics (Mail + Express & Parcels)	472,223	3.48
Financial Services	181,586	1.34
Real Estate (73.7% stake	113,086	0.83
Banco CTT (91% stake)	139,372	1.03
Adjustments	-187,343	-1.38
Expected Net Value from the acquisitions	81,507	0.60
Expected Net Value from Bank-Spin Off	169,500	1.25
Estimated Equity Value	**969,931**	**7.16**
Current Equity Value	924,173	6.82
Upside / Downside	5.0%	0.00
Recommendation	**HOLD**	

***Source**: Team Estimates*

Figure B1: Price Target Distribution (€/sh.)



***Source**: Team Estimates*

HOLD is our recommendation for CTT – Correios de Portugal, SA with a price target of €7.2/sh for 2025YE using a DCF model, with a Sum-of-the-Parts (SoP) approach. Our forecast implies a 5.0% upside from the March 12th, 2025, closing price of €6.8/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.

Sights are set on the Iberian e-commerce potential

Recent developments made it clear: CTT's focus is now on the expansion in Iberian e-commerce of which the Group aspires to be a comprehensive logistic player. The recent announcements of the acquisition of the Spanish CACESA and the Joint Venture (JV) with DHL for Iberia are the crystallization of this commitment. We estimate that both transactions, announced in December 2024, are estimated to yield a net value of €81.5M (€0.60/sh). The decision to acquire a leading company specialized in cross-border ecommerce flows and with relevant exposure to the Spanish market aligns with the CTT Group strategy and is a sharp move considering the changing European regulation on cross-border import. Both these transactions are estimated to add €175M of top-line growth in FY26 (+35% on the E&P stand-alone scenario) and improve EBIT margin by up to 12% (+200 bps) in FY29. However, margin enhancements are expected to transpire upon the development of estimated cost synergies. The success of the integration of CACESA is crucial in this regard and poses a layer of uncertainty. CACESA emerged as a top target in Iberia, confirming the reliability of the target prediction framework detailed in the supplementary analysis and reenforcing the positive outlook for CTT, contingent on successful integration.

CTT wants to focus on packages, not on the Bank

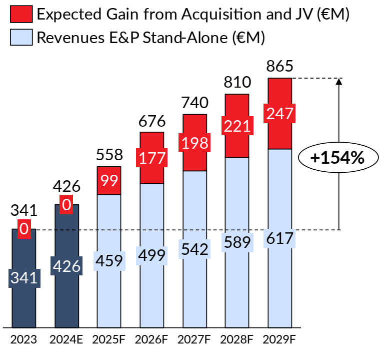
CTT is sharpening its focus on Express & Parcels and Logistics to capitalize on e-commerce growth, aiming to become a full-service logistics provider in Iberia. The November 2024 sale of an 8.7% stake in Banco CTT to Generali enhances liquidity for strategic acquisitions. Banco CTT remains a strong candidate for future deals, with potential proceeds, possibly at a premium, likely reinvested to support CTT's logistics shift. We estimate a bank spin-off could yield a net value of €169.5M (€1.25/sh.).

Cost-Saving Challenges: Lost in Transit?

CTT continues to prioritize cost reduction through automation, with planned CAPEX at c.3% of Sales and 25% of EBITDA from 2023–2029. However, progress has been uneven, largely due to its reliance on Portugal's Mail network. Mail-related costs, driven by regulatory constraints, have exceeded 90% of OPEX/Sales since FY23, significantly limiting CTT's ability to optimize expenses. While there are scalability opportunities in Spain, regulatory constraints in the Mail business pose a major obstacle to effective cost reduction.

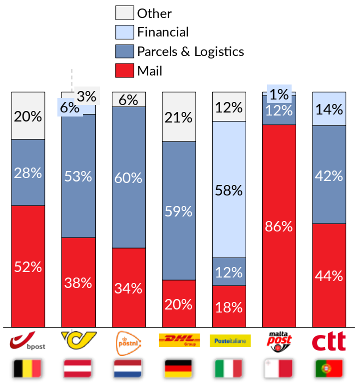
Differentiation through Banco CTT and Financial Services | Banco CTT and Financial Services provide differentiation within CTT's portfolio. While Banco CTT offers strategic optionality, particularly through a potential spin-off, its growth remains constrained by a narrow loan portfolio. In contrast, Financial Services deliver strong profitability (58% recurring EBIT margin in FY23), though performance is closely tied to public debt market dynamics.

Figure B2: Revenue from Acquisitions



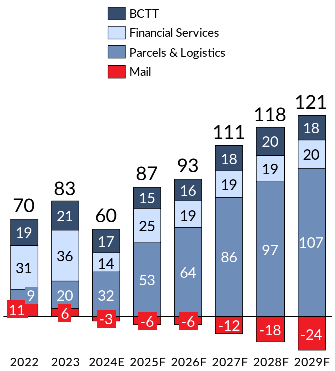
Source: Team Estimates

Figure B3: Differentiation vs. Other Postal Operators in Europe (FY24) – Revenue Breakdown by Segment (in%)



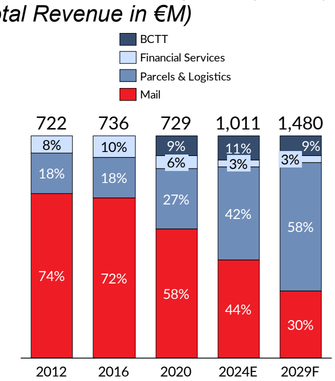
Source: Refinitiv Eikon

Figure B4: Recurring EBIT FY23 per Segment (€M)



Source: Team Estimates

Figure B5: Revenue per Segment (% of Total Revenue in €M)



Source: Team Estimates

Valuation Methods | We used a DCF model based on SoP FCFE applying different cost of equity per segment and reached a €7.2/sh price target.

Risk to the Price Target | Buying this 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 integration after the future acquisition. Competition is also relevant for (iii) the FS and (iv) Banco CTT along with the exposure to market conditions.

Business Description

CTT – Correios de Portugal is a Portuguese logistics operator, primarily focused on the deliveries of mail, parcels, and with complementary business in the financial services industry. Founded in 1520 by King Manuel I of Portugal, the company operates in the Iberian Peninsula. In 2015 the company tried to exploit the financial sector thanks to its solid footprint in Portugal with 569 physical locations, founding Banco CTT (present in 212 branches).

CTT reported €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).

Digitalization and sustainability are two megatrends 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.

Operational segments

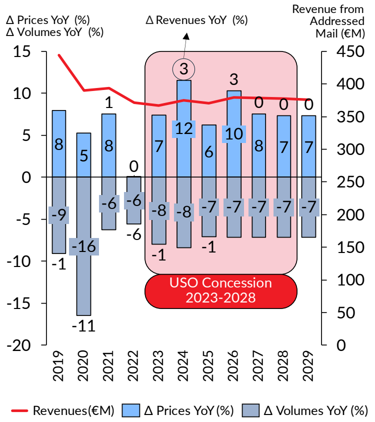
Mail & Others | The Mail segment is divided into Addressed Mail (Transactional, Advertising, and Editorial) and Unaddressed Mail. CTT manages 80% of the Postal Traffic in Portugal, with around 55 thousand customers served daily (FY23 -16% YoY) and an average of 4.4 thousand residents per access point. The main issue lies in the sharp drop in Mail Volumes -202M items FY23 (-8% YoY for Addressed Mail, -39% YoY for Unaddressed Mail). Addressed Mail volume is expected to continue declining, with a projected CAGR of -7% from FY24 to FY29. Pricing is regulated by conventions with ANACOM and has mirrored volume drops to balance top-line revenues for this segment at a stable stream, however, challenges may arise due to possible rising costs from Universal Service Obligations.

Express & Parcels (E&P) | CTT primarily offers B2C last-mile solutions in Portugal (39% of Total Volumes FY23), Spain (61%), and Mozambique (0.1%). Yet, the company is shifting towards an Iberian business model, exemplified by the €104M acquisition of Spanish CACESA in December 2024, which specializes in international e-commerce customs clearance across 15 countries. With operations based in Madrid, CTT achieves 24-hour delivery across the Iberian Peninsula by sorting and clearing parcels in-house.

In FY23, this business unit generated €341M in revenue (+31% YoY), marking the highest growth among CTT's four BUs. The E&P business unit has also improved profitability, increasing its EBIT margin from -0.3% FY20 to 5% FY23. The CACESA acquisition is expected to add €87M to revenues and €17M to EBIT.

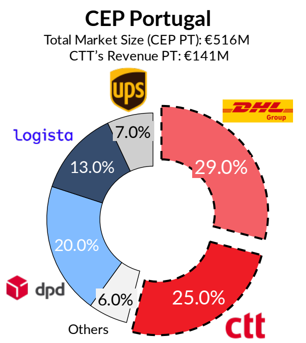
CTT entered Spain in 2005 with the acquisition of Tourline Express (€28M), marking its entry into the CEP sector. Its Spanish operations saw significant growth in FY23 and 24Q1, with Spanish E&P revenue (€186M) surpassing Portugal's (€149M) for the first time. This highlights the scalability of CTT's Spanish business, where its market share stands at approximately 4% in Revenues. The CACESA acquisition will allow CTT to grow this share to around 5.5%. In Portugal, CTT holds a stable 50% market share, positioning the company to capture e-commerce growth, possibly enhanced by DHL JV, while maintaining its leadership. The footprint of the Mail & Others segment is detrimental to this share.

Figure B6: Mail Segment Details



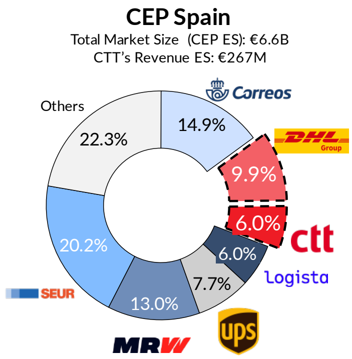
Source: Team Estimates

Figure B7: Courier, Express & Parcels (CEP) Industry: Market Share in Portugal FY24



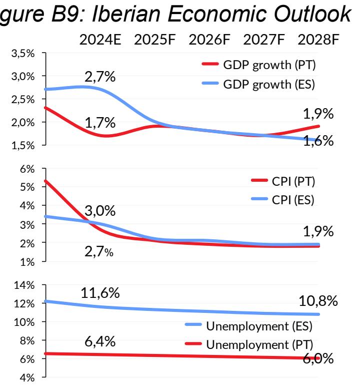
Source: Team Estimates

Figure B8: Courier, Express & Parcels (CEP) Industry: Market Share in Spain FY24



Source: Team Estimates

Figure B9: Iberian Economic Outlook



Source: EIU

Financial Services & Banco CTT | CTT's Financial Services segment earned €63M in FY23 with a 58% EBIT margin, mainly from Savings & Insurance via government certificates and Generali partnerships. It uses CTT's network to deliver simple financial solutions. Banco CTT, established in 2016 (91% owned by CTT, 9% by Generali), generated €148M in FY23 revenue (+17% YoY), driven by strong growth in net interest income from auto and mortgage loans. Leveraging CTT's branch network, it targets continued expansion.

Real Estate | CTT's Real Estate operations, led by subsidiary CTT IMO Yield, focus on enhancing asset value through the Lego Project with Sonae Sierra, targeting logistics expansion and tenant diversification. In January 2024, CTT sold a 26.3% stake in IMO Yield to Sonae Investments and others, supporting strategic growth.

Adaptability creates opportunity

In May 2024 CTT CEO João Bento outlined a clear strategy to consolidate the E&P segment through M&A deals, particularly targeting logistics and last-mile delivery firms in Spain.

Supported by a CAPEX plan of €160M-€180M for FY22-FY25, this approach aims to capitalize on the booming e-commerce market and drive automation and efficiency.

At the end of 2024, CTT announced two pivotal transactions to strengthen its e-commerce logistics leadership in Iberia, both subject to regulatory approval. The acquisition of CACESA, valued at €104M (EV: €91M, 5.5x EBIT), expands CTT's presence in cross-border e-commerce and customs clearance. CACESA generated €87M in revenue (+69% YoY) and €17M in EBIT (+117% YoY) in FY23, with synergies expected to add €5M EBIT (c.-167bp) post-integration (via cost reduction). The deal, financed through debt, will maintain leverage below 2.5x (Net Debt/EBITDA) and is set to close by 1H25. Concurrently, CTT has entered a JV with DHL, combining CTT Express' 20K service points, 22 hubs, and 1K lockers with DHL's 3K points, 7 hubs, and 73 depots. The JV targets €35M annual synergies via optimized facilities, linehaul, and last-mile operations, boosting Iberian B2C and B2B capabilities. The transactions in which DHL would acquire a 25% stake in CTT Express and CTT would take 25% of DHL Parcel Iberia could result in net cash proceeds to CTT in the amount of €69M.

Company Strategies: Maintain market leadership in mail and parcels | Despite its declining trend, the Mail & Others BU remains the top revenue segment, although negative in the bottom line. CTT is advocating for a regulatory framework that supports USO sustainability and quality standards. At the same time, the group is capitalizing on strong e-commerce growth, particularly in the B2C segment, leveraging its position in Portugal. Expanding its network, especially through Lockers, is key to unlocking future growth.

Key drivers of profitability: Leveraging Infrastructure for 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.

Industry Overview & Competitive Positioning

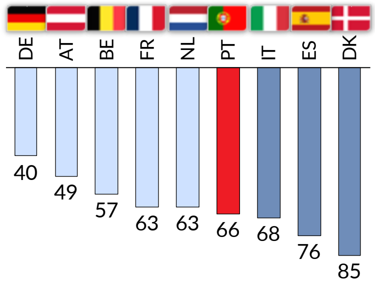
Iberian Economic Outlook and Geopolitical Instability

Portugal's economy is projected to grow 1.7% in 2024 and 1.9% in 2025, with Spain at 2.7% and 1.6% respectively, driven by consumption and investment. Inflation is expected to ease, while unemployment is predicted to remain stable. However, external risks persist. Ongoing geopolitical instability, particularly in Ukraine and the Middle East, along with central bank policy shifts and supply chain disruptions, pose significant challenges. Additional volatility stems from political uncertainty in France, Germany, and potential economic impacts from recent U.S. elections, all of which affect business unit performance.

Market Overview: Different Industries with Dynamic Outlooks

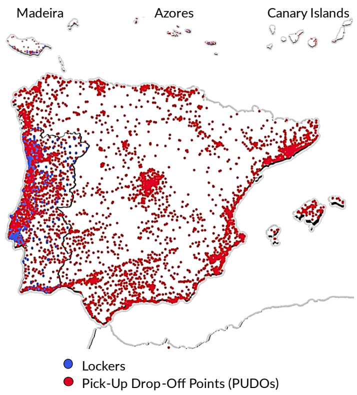
Postal operators across Europe are facing significant challenges, with a 45% decline in the EU15's postal traffic in the period 2008-2023, (PT stands around a 63% decline, according to UPU and McKinsey. Market liberalization has failed to attract players able to meet strict quality standards in terms of price, density, and service. ANACOM recently asked for more

Figure B10: Last 20 yrs (2005-2024) Mail Volume Decline in % – European Countries



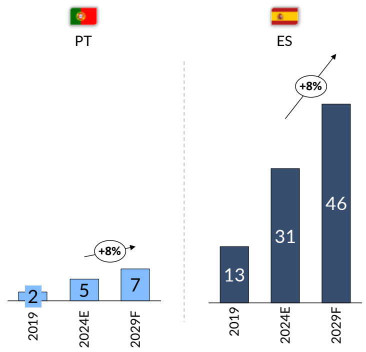
***Source**: National Communication Authorities*

Figure B11: Network Capillarity



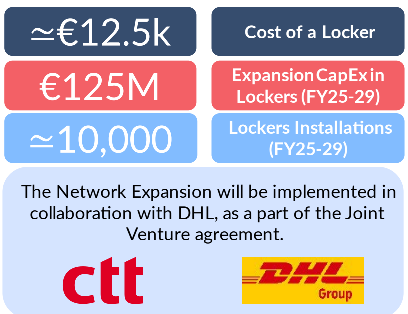
***Source**: CTT Annual Reports*

Figure B12: Evolution of e-Commerce Sales (€B) in Portugal and Spain with CAGR



***Source**: Euromonitor International*

Figure B13: Automation and Network Expansion



***Source**: Team Estimates*

players in the market but there are no relevant margins to attract the appetite for other players. It is not an appealing business to enter. The need for regulatory reform seems inevitable in the medium term. The case of PostNord Denmark, which faced a 90% reduction in the Mail Volumes from the start of the millennium represents what CTT and the other postal operators want to avoid. PostNord decided to end its USO concession at the beginning of 2024 after years of unprofitability and subsidies from the Danish government. However, relative differences between PT and other more developed and digitalized countries may provide a buffer over the next years. Another buffer comes from a diversified portfolio of the CTT group.

On the contrary, the **Express & Parcels Couriers** market has been on the rise. Steady growth is driven largely by global demand growth in e-commerce (+14.6% in PT and +10.3% in ES expected Sales growth by the end of 2024) and increasing consumer expectations for fast and reliable deliveries. The e-buyers in 2024 are estimated to be 5.3M in PT and 26.3M in ES representing respectively 50% and 54% of the population. The e-buyer participation is persistent with >94% purchasing goods at least every 3 months. A key trend shaping the market is the emergence of the "Super Shopper" a highly engaged, tech-savvy ecommerce consumer with significant purchasing g power, frequently buying across multiple categories (20+ transactions per year). The main reason to buy online is the "ease of purchase" (for 73.6% PT and 71.3% ES of the e-buyers). On the other side, the e-sellers are focused on three strategic pillars: (i) environmental sustainability, (ii) increasing investment in digital media, and (iii) prioritizing the offer of free shipping. The Financial Services industry is a broad market, which comprises a mix of banking and non-banking activities, as well as intermediation of insurance.

Demand Drivers

Economic Activity and Demographics | Higher levels of economic activity drive an increase in transactional mail volumes. However, digitalization is steadily reducing this demand at a high single-digit rate every year, ensuring a decline in traditional mail services leading to a floor in the upcoming years. Demographic changes will further reinforce this trend, with an increasing preference for digital solutions.

E-commerce growth | Demand for parcel delivery is driven by growth in consumer spending and overall economic activity, as reflected in the growth of E-commerce Retail Sales forecasted by Euromonitor International (CAGR 24-28: +8% for both PT and ES). Digitalization is amplifying this upward trend in ecommerce demand. In particular, according to McKinsey, Cross-border e-commerce is growing 1.5 times faster than Domestic orders with China accounting for almost 45% of Inbound orders to Spain and Portugal, making it the most relevant country for imports, as noted by DHL.

Supply Drivers

Quality Targets and Regulatory Outlook | Regulatory frameworks established through agreements with national authorities require the company to comply with 8 quality standards (reduced from 24), as defined in 2023. These revised standards, coming into effect by the beginning of 2025, focus on pricing, density, and overall service quality.

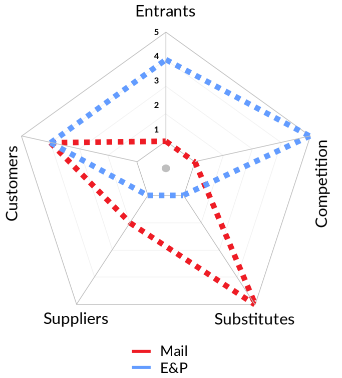
UnLockying Tomorrow's Solutions—Automation and Network Expansion | Free shipping, timely and fast deliveries, and the strategic use of delivery points are the key drivers of an efficient Courier machine. To stay ahead of competitors, investments in innovative IT technologies, advanced Computer Software are essential to increase the horsepower of one's own engine, enabling a more efficient sorting and clearing mechanism. CTT's acquisition of Cacesa and Expansion CAPEX of €20M adds fuel to the engine in this sense. Moreover, the introduction of Lockers (PT: 990 installed and 1182 contracted | ES: 8 installed and 54 contracted) represents a direct shortcut to the delivery routes, giving Couriers the ability to deliver directly to the Out-Of-Home (OOH) point, instead of time-consuming door-to-door deliveries optimizing operating costs. According to McKinsey, OOH development is expected to catalyze 20%-30% of total parcel volume in 2027, with a corresponding cut in OPEX by 10%-20% for the CEP players.

Competitive Positioning- Offsetting Threats between Businesses

Rivalry Among Existing Competitors | Mail: Low | E&P: High

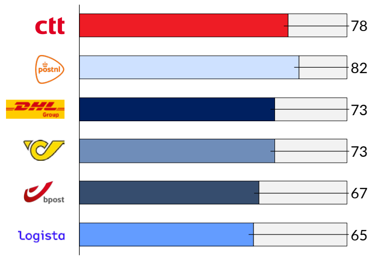
CTT faces low rivalry in Mail, holding over 80% market share and a de facto monopoly. In E&P, competition is intense, with 50% market share in PT and 6% in ES, competing with established players like DHL and DPD, though recently partnering strategically with DHL.

Figure B14: Porter's 5 Forces Analysis



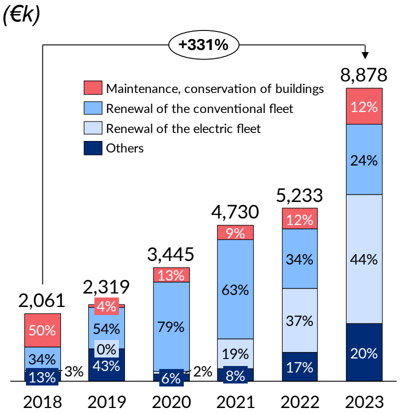
Source: *Team Estimates*

Figure B15: ESG Score vs. Peers



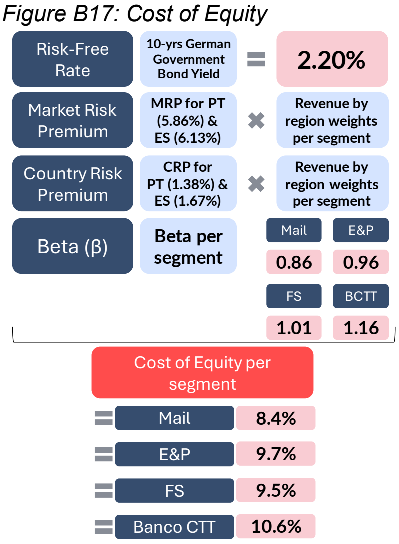
Source: *Refinitiv Eikon*

Figure B16: Environmental Investment (€k)



Source: *CTT Annual Reports*

Figure B17: Cost of Equity



Source: *Team Estimates*

Threat of Substitute Products | Mail: High | E&P: Low

Digitalization is reshaping consumer behavior, increasing substitute threats in Mail which is partially offset by the E&P trend. This segment remains comfortable regarding substitutes as standardized logistics are vital for e-commerce-driven timely delivery.

Bargaining Power of Suppliers | Mail: Low | E&P: Medium

In Logistics, supplier power is moderate due to reliance on inputs like fuel, vehicles, and warehouses, especially in Spain.

Bargaining Power of Customers | Mail: Low | E&P: High

In Mail, customer influence is negligible, with corporate clients leading price and service talks. In E&P, competition and low differentiation grant buyers significant leverage.

Threat of New Entrants | Mail: Low | E&P: Moderate

In Mail, high infrastructure costs, regulations, and CTT's 80% market share create significant entry barriers, maintaining its monopolistic dominance. E&P entry requires relevant capital needs and complex logistics.

ESG

CTT's focus on transparency and sustainability enhances investor appeal. With a strong Refinitiv ESG Score of 78, it outperforms many European postal peers. In 2023, 72% of revenue came from taxonomy-eligible activities, with 30% of CAPEX and 49% of OPEX aligned.

Environmental

CTT has successfully reduced total CO2 emissions by 2.6% since 2022, meeting its short-term targets. However, there has been an 18.8% increase in parcel-related emissions. The plans include electrifying 50% of last-mile vehicles by 2025 (100% by 2030). In 2023, electric vehicles made up 19.6% of the fleet. Despite a 68.1% increase in waste from Asian parcels, waste recovery remained at 99.3%. Environmental investment increased to €9 million, representing a 331% growth since 2018. The company holds ISO 14001 certification, attesting to its commitment to environmental management.

Social

In 2023, CTT's turnover rate was 18.7%, and contracting rose to 37.5%. While the target for gender parity among middle managers has not been met (37% female), the target for senior management has been reached, with 50% parity and a gender pay ratio of 0.77. The company has achieved this by exceeding targets for volunteer hours, and by successfully negotiating reduced labour strikes. These achievements have contributed to CTT being ranked as the best company in its sector to work for.

Governance

CTT has a dispersed shareholder structure, with a 51.6% free float. A €25M share buyback (up to 6.14%) is underway. In 2024, CTT contested a €400k fine for service failures. The current board has reduced executive and non-executive members, slightly increased independence, and maintains 36% female representation. The Executive Committee is experienced and stable. Executive pay includes fixed and variable components (37.2% variable), while non-executives receive fixed compensation only.

Valuation

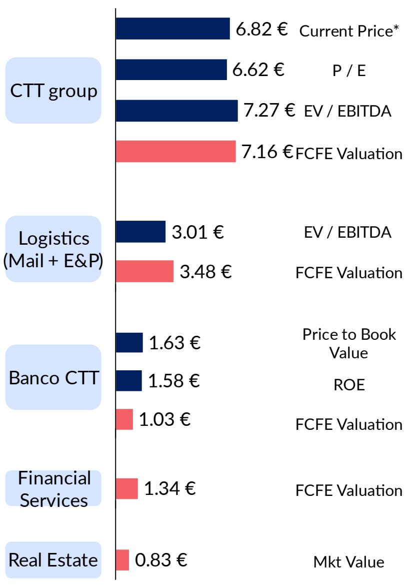
Free Cash Flow to Equity (FCFE): a Sum of the Parts (SoP) Approach – Connecting the Dots | CTT's valuation employs a Free Cash Flow to Equity (FCFE) Sum-of-the-Parts (SoP) approach, reflecting the diverse nature of its operations and the unique growth and risk profiles of each segment. The Mail segment is valued with a 0% terminal growth rate, recognizing its mature, declining status, while E&P (Express & Parcels) is assigned a 2% growth rate aligned with Iberian economic forecasts. Banco CTT is valued using an equity approach with a 2% growth rate, reflecting its banking operations, and Financial Services is capped at 1%, given its dependence on mail infrastructure and external factors. The Real Estate segment is valued at market value. Strategic developments, including the December 2024 acquisition of CACESA

Table B2: Valuation Table

CTT Group Equity	Method	€k	€/sh.
Equity Value by Segment			
Logistics (Mail + Express & Parcels)	FCFE	472,223	3.48
FS	FCFE	181,586	1.34
Real Estate (73.7% stake)	Mkt Value	113,086	0.83
BCTT (91% stake)	FCFE	139,372	1.03
SoP Equity Value		906,267	6.69
Contingent Liabilities	9M24 BV x 75%	-8,421	-0.06
Pension Obligations not included in cash flows	Actuarial Value 9M24	-178,922	-1.32
SoP Equity Value Base Case Scenario		**718,925**	**5.31**
Acquisition Impact			
Increase in Value with Cacesa's Acquisition	Δ FCFE	99,063	0.73
Payment to Cacesa Net of Cash Proceeds from DHL JV	Transaction	-35,000	-0.26
DHL Parcel Iberia Stake (25%)		26,500	0.20
Net Value from the acquisitions		90,563	0.67
Probability of Approval from Regulators	Upon Approval	90%	
Expected Net Value from the acquisitions		**81,507**	**0.60**
Acquisition Impact			
IPO Bank Re-Valuation	Mkt Value	126,000	0.93
Spin-Off Costs	Team Estimate	-15,000	-0.11
Re-Rating CTT Group	Mkt Value	115,000	0.85
Likelihood	Probability	-56,500	-0.42
Expected Net Value from Spin-Off / IPO		**169,500**	**1.25**
SoP Equity Value with Acquisitions	**2025 YE**	**969,931**	**7.16**
Shares Outstanding	thousands	135,509	
Current Equity Value	As of Mar 12, 2025	924,173	6.82
Upside / Downside		5.0%	
Cost of Equity		9%	
Recommendation	**HOLD**		

***Source**: Team Estimates*

Figure B18: Valuation Methods



***Source**: Team Estimates, Refinitiv Eikon*

and a joint venture with DHL, are incorporated through scenario analysis. Furthermore, given the likely Banco CTT spin-off, the group was also revalued using Logistics sector multiples.

Cost of Equity | The Group is exposed to several risk factors that cannot be captured in a single discount rate. Therefore, different cost of equity figures for each business segment. The normalized 10-year German Government Bond Yield (2.20%) sets the riskless asset. Using the pure-play approach to compute

the different 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. In the case of E&P, we computed a revenue-weighted average MRP and CRP for Spain in and Portugal (respectively 6.13% and 1.67%), to capture the different risks of the two countries where the operations are carried out.

Revenue Forecast

Mail | The forecast projects stable revenues (CAGR24-29: +0.2%) based on historical trends in Mail Volumes in PT and the current USO concession formula, valid beyond FY29. A SARIMA model captures future volume decline, resulting in a negative CAGR for Addressed Mail Volumes (-7.2%), aligning with EU benchmarks.

E&P | E&P sales in ES and PT are driven by forecasted 8% CAGR 2024-28 in e-commerce retail sales, moderating to 6% by FY29 in line with EU growth. CTT's market share is another key factor, with 50% in PT and 6% in ES in FY2024 due to high service quality. ES market share is expected to remain stable at 6% without considering potential synergies from the acquisition, which will strengthen CTT's position in the Spanish CEP market.

E&P 2.0 – Value added from CACESA acquisition and DHL Joint Venture | The additional value added to E&P of €81.5M is estimated, assuming a 90% chance of regulatory approval. The CACESA acquisition and DHL JV provide CTT with more airport sorting facilities and enable synergies in B2B and B2C last-mile distribution. These deals are expected to raise market share to 56% nationally and 5.5% in Portugal and Spain by FY29, while improving margins with a global OpEX reduction of 167bps starting FY26.

Margins | Automation boosts E&P margins, with costs declining. External Supplies and Services (ES&S) drop c.200 bps from 77% in a few years, excluding synergies from CACESA acquisition and DHL partnership. Dis-synergies occur in 2025-26, especially on ES&S and Staff Costs. Synergies generate 167 bps cost savings compared to 2023.

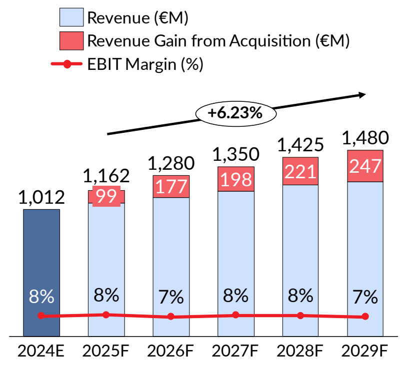
Adjustments: Contingent Liabilities and Pension Liabilities | Contingent liabilities result in an estimated €8.4M (-0.06 €/sh.) figure. Pension liabilities do not have the corresponding assets, thus there is a full negative funded status. As our SoP approach to cash flows and valuation disregards this responsibility, the FY24 actuarial value of €178M (-1.32 €/sh.) is adjusted in the valuation.

Alternative Methods - Relative Valuation Analysis | A relative valuation was conducted for CTT's Mail and Express & Parcels (E&P) segments using market-based multiples, specifically EV/EBITDA and P/E, to benchmark against comparable peers. Peer groups were selected from Refinitiv Eikon's Courier, Postal, Air Freight & Land-based Logistics industry, further refined by subindustry (Postal Services for Mail and Logistics for E&P), and filtered through a qualitative screen based on operational comparability and relevant financial ratios. Peer valuation was conducted for the broader Logistics business (Mail + E&P), based on LTM EBITDA of €80.5M, debt of €232.7M, and cash of €53.3M, as well as for the entire CTT group, with LTM EBITDA of €146.30M and the same debt and cash figures. Full peer selection methodology is detailed in Appendix B8.

Financial Analysis

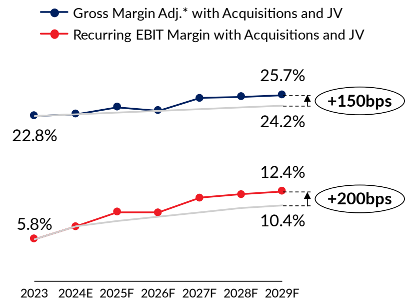
Top-line Revenue growth - E&P is surfing the wave of e-commerce wave growth | CTT achieved a notable 6.6% CAGR in overall top line growth Revenues from FY19 to FY23. Looking ahead, revenues are projected to grow at a CAGR of 6.2% from FY25 to FY29, significantly boosted by the recent acquisitions and partnerships scenario (+2.2% on CAGR 25-29). While the traditional Mail business continues to contribute significantly to the top line albeit not a profitable business, the diversification efforts are increasingly taking precedence. Moreover, recent trends and acquisition are reshaping the geographic Revenue composition, with the Spanish share of CTT revenues Spain's share expanding significantly from 19% FY23 to 36% of total revenue by FY29.

Figure B19: Top-line Revenue Growth and EBIT Margin



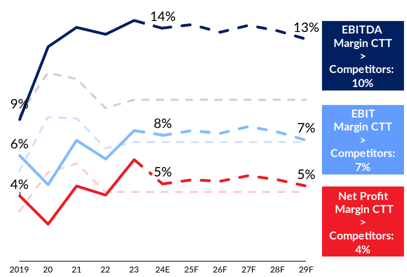
Source: *Team Estimates*

Figure B20: Margins' Enhancement with Acquisitions



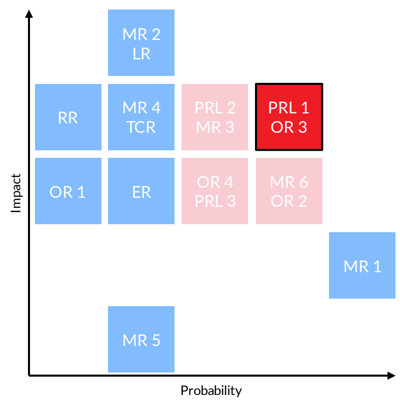
Source: *Team Estimates*

Figure B21: Profitability vs. Iberian Competitors in E&P



Source: *Team Estimates*

Figure B22: Risk Matrix



Source: *Team Estimates*

Profitability pressured by Mail, Sustained by E&P | CTT's EBITDA margin is forecast to be between 13% and 15% from FY21 to FY29, placing the Group on the peer industry average of 13%. However, the declining Mail segment continues to have a significant impact on profitability, as it is the Group's main cost center, with OPEX/Sales approaching c.98% by FY29. This structural pressure is making margin improvement increasingly difficult and is contributing to the expected decline in ROE from 24% in FY23 to 14% in FY29, despite a steadier ROIC path (from 12% to 8%). In contrast, the Express & Parcels segment is set to enhance Group profitability, with revenue growth and operational leverage driving an EBITDA margin of 12% by FY29, up by +123bps from FY24 and above Iberian competitors. EBIT margin is forecast to improve by +292bps, underpinned by past investments and asset rotation, especially in Spain, with Fixed Asset Turnover projected to reach 4x.

Excess Cash for Acquisitions | As highlighted in the supplementary analysis to this Equity Research, CTT's strong liquidity position was a key driver for exploring potential future M&A opportunities. JB Capital Markets estimates excess cash of approximately €120M by 2025, indicating that CTT is well-positioned to pursue strategic acquisitions without the need for additional debt financing. This robust cash buffer served as a central rationale for conducting the additional study on acquisition potential.

Investment Risks

OR 4 | Operational Risk | Implementation Joint Venture & Acquisition

The realization of synergies is uncertain, particularly in light of CTT's expansion into new ventures like Cacesa and the geographically dispersed nature of its operations, which adds significant management complexity. Similarly, the Joint Venture with DHL is expected to solidify CTT's position as the largest player in the Portuguese CEP market, with an estimated market share of approximately 34% for CTT Express once the Joint Venture becomes operational. However, this could also signal potential challenges in sustaining such a market share over the long term.

PRL 1 | Political, Regulatory and Legal Risk | Taxes & Tariffs

The European Commission is considering the abolition of the current IOSS (Import One Stop Shop) that allows third-party countries a simplification on the VAT payment collected by the seller during the purchase. The VAT will be then collected by customs at import. Moreover, the Commission is planning to abolish the €150 custom duty exemption, with effect from March 1, 2028. This change can have a potentially high impact on the final customers, discouraging them from buying goods online that are likely going to be more expensive. CTT curtails these risks by controlling the value chain with its own clearing house.

PRL 1 | Political, Regulatory and Legal Risk | Taxes & Tariffs (update)

The logistics industry is expected to face material headwinds stemming from escalating geopolitical trade tensions, particularly the anticipated imposition of new U.S. tariffs. These measures are likely to prompt a strategic realignment by major Chinese e-commerce firms, many of which are already exploring a pivot toward the European market in response to tightening access to U.S. consumers. However, this potential shift coincides with the European Union's introduction of more stringent regulatory frameworks, which could pose additional operational and compliance challenges for cross-border logistics providers. The near-term outlook remains uncertain, as stakeholders await definitive policy decisions from the United States, the European Union, and China regarding tariffs and trade regulations. As a result, logistics firms with exposure to international e-commerce flows should closely monitor policy developments and assess contingency strategies to mitigate potential disruption.

OR 3 | Operational Risk | Staff Retention

The E&P business is highly seasonal, the peak season starts with Black Friday and ends with the Christmas sales (both these events represent in Q4 c. 35.5% PT and 26.8% ES of sales for the e-seller). Keeping up with the demand during this period requires additional employees, with a seasonal contract. The reputation and the attractivity of CTT in the job market are relevant in this phase. Recent awards suggest CTT has mitigating factors, but seasonal labor shortages during peak demand can still impact growth and service quality.

9 Appendix C: CTT's Equity Research Supplementary Materials

The main work can be read independently of these Appendices, although they provide a better understanding of the analysis. The valuation of other CTT segments is outside the scope of this MFW, as it focuses primarily on the Mail and E&P segments, with particular attention to the strategic acquisitions undertaken by CTT.

Appendix C1 - Consolidated Financial Statements:

Consolidated Income Statement (€k)	2022	2023	2024E	2025F	2026F	2027F	2028F	2029F	CAGR 25-29	2024E % Rev	2029F % Rev
Revenues	**906,625**	**985,219**	**1,011,565**	**1,158,903**	**1,288,196**	**1,354,913**	**1,427,590**	**1,479,703**	**6%**	**100%**	**100%**
Sales and services rendered	788,582	844,606	895,414	1,043,781	1,167,760	1,228,294	1,294,300	1,345,944	7%	89%	91%
Financial margin	74,357	98,791	91,258	89,416	93,828	99,035	104,751	106,113	4%	9%	7%
Other operating income	43,686	41,821	24,893	25,707	26,608	27,583	28,539	27,646	2%	2%	2%
Operating costs	**(850,498)**	**(907,441)**	**(934,491)**	**(1,066,971)**	**(1,188,379)**	**(1,244,126)**	**(1,315,562)**	**(1,370,994)**	**6%**	**-92%**	**-93%**
External supplies and services	(343,216)	(394,021)	(412,506)	(508,849)	(603,329)	(639,283)	(689,370)	(727,932)	9%	-41%	-49%
Staff costs	(358,237)	(365,020)	(395,394)	(419,146)	(440,414)	(454,639)	(470,030)	(483,883)	4%	-39%	-33%
Other Operating Costs	(80,632)	(82,665)	(61,192)	(65,026)	(66,183)	(67,698)	(69,360)	(69,287)	2%	-6%	-5%
EBITDA	**124,540**	**143,513**	**142,473**	**165,882**	**178,270**	**193,293**	**198,830**	**198,601**	**5%**	**14%**	**13%**
Depreciation/amortization	(68,413)	(65,735)	(65,399)	(73,950)	(78,452)	(82,507)	(86,802)	(89,891)	5%	-6%	-6%
EBIT	**56,127**	**77,778**	**77,075**	**91,932**	**99,818**	**110,786**	**112,028**	**108,710**	**4%**	**8%**	**7%**
Financial results	(9,413)	(16,240)	(12,638)	(13,951)	(14,996)	(15,740)	(16,809)	(17,685)	6%	-1%	-1%
EBT	**46,714**	**61,538**	**64,436**	**77,982**	**84,821**	**95,047**	**95,219**	**91,025**	**4%**	**6%**	**6%**
Income tax	(10,372)	(1,096)	(17,071)	(20,527)	(22,273)	(24,922)	(24,931)	(23,800)	4%	-2%	-2%
Net profit for the period	**36,342**	**60,442**	**47,366**	**57,454**	**62,548**	**70,125**	**70,288**	**67,225**	**4%**	**5%**	**5%**
Equity holders	36,407	60,511	46,712	50,362	54,276	60,562	59,331	55,248			
Non-controlling interests	(64)	(69)	653	7,092	8,273	9,563	10,957	11,977			
Earnings per share:	0.25	0.43	0.35	0.39	0.42	0.47	0.47	0.44			

Consolidated Balance Sheet (€k)	2022	2023	2024E	2025F	2026F	2027F	2028F	2029F	CAGR 25-29	2024E % Assets	2029F % Assets	Notes
Tangible fixed assets	303,206	296,995	331,712	323,332	302,747	291,636	284,693	275,770	-4%	6%	4%	see Asset Schedule
Investment properties	6,184	5,976	6,051	6,051	6,051	6,051	6,051	6,051	0%	0%	0%	
Intangible assets	69,409	70,640	71,347	70,599	68,788	65,553	60,894	54,811	-6%	1%	1%	see Asset Schedule
Goodwill	80,257	80,257	80,257	164,602	164,602	164,602	164,602	164,602	0%	1%	2%	
Investments in joint ventures	-	22	22	22	22	22	22	22	0%	0%	0%	
Financial assets at fair value through profit or loss	26,220	13,532	14,094	14,794	15,560	16,522	17,347	18,230	5%	0%	0%	
Debt securities at amortized cost	409,389	364,706	382,024	400,997	421,767	447,848	470,202	494,133	5%	7%	7%	see BCTT details
Other non-current assets	70,925	78,130	78,130	80,121	80,121	80,121	80,121	80,121	0%	1%	1%	
Credit to banking clients	1,287,676	1,444,412	1,492,786	1,556,575	1,626,993	1,718,230	1,793,461	1,874,316	5%	27%	26%	see BCTT details
Total non-current assets	2,253,265	2,354,670	2,456,424	2,617,093	2,686,651	2,790,586	2,877,394	2,968,056	3%	44%	42%	
Inventories	8,041	6,663	11,171	13,649	16,081	17,026	18,330	19,328	9%	0%	0%	see NWC Schedule
Accounts receivable	147,131	153,062	163,388	171,260	179,453	187,071	194,917	199,595	4%	3%	3%	
Credit to banking clients	489,889	148,802	164,330	171,352	179,103	189,147	197,429	206,330	5%	3%	3%	
Debt securities at amortized cost	128,392	364,760	1,560,749	1,828,865	1,899,911	1,978,263	2,022,450	2,145,760	4%	28%	30%	
Other current assets	113,076	102,501	102,493	102,493	102,493	102,493	102,493	102,493	0%	2%	1%	
Other banking financial assets	461,226	1,274,575	770,044	599,608	679,203	785,230	885,632	898,053	11%	14%	13%	see BCTT details
Cash and cash equivalents	456,469	351,610	380,959	428,390	506,083	524,938	559,409	583,482	8%	7%	8%	
from CF (excl. BCTT)			*302,352*	*348,022*	*423,787*	*440,222*	*472,619*	*494,470*	*9%*	*5%*	*7%*	
from BCTT BS			*78,607*	*80,368*	*82,295*	*84,716*	*86,790*	*89,011*	*3%*	*1%*	*1%*	
Total current assets	1,804,224	2,401,972	3,153,134	3,315,617	3,562,326	3,784,167	3,980,660	4,155,039	6%	56%	58%	
Total assets	**4,057,488**	**4,756,642**	**5,609,557**	**5,932,710**	**6,248,977**	**6,574,752**	**6,858,053**	**7,123,096**	**5%**	**100%**	**100%**	
Consolidated Balance Sheet (€k)	**2022**	**2023**	**2024E**	**2025F**	**2026F**	**2027F**	**2028F**	**2029F**	**CAGR 25-29**	**2024E % Assets**	**2029F % Assets**	**Notes**
Share capital	72,675	71,958	69,220	69,220	69,220	69,220	69,220	69,220	0%	1%	1%	
Own shares	(10,826)	(15,625)	(8,948)	(18,948)	(28,948)	(38,948)	(48,948)	(58,948)	33%	0%	-1%	
Reserves	53,844	48,113	30,510	30,510	30,510	30,510	30,510	30,510	0%	1%	0%	
Retained earnings	64,647	83,269	119,951	145,643	172,838	202,147	238,484	274,083	17%	2%	4%	see Equity Schedule
Other changes in equity	6,857	3,402	3,409	3,409	3,409	3,409	3,409	3,409	0%	0%	0%	
Net profit	36,407	60,511	47,366	57,454	62,548	70,125	70,288	58,434	0%	1%	1%	
Equity attributable to equity holders	223,603	251,629	261,508	287,289	309,578	336,464	362,964	376,708	7%	5%	5%	
Non-controlling interests	1,326	1,624	33,564	34,217	41,309	49,582	59,145	70,102	20%	1%	1%	
Total equity	**224,929**	**253,253**	**295,072**	**321,506**	**350,888**	**386,046**	**422,109**	**446,811**	**9%**	**5%**	**6%**	
Medium and long term debt	136,198	161,080	195,899	228,086	245,118	265,775	273,389	273,073	5%	3%	4%	see Debt Schedule
Employee benefits	185,258	149,740	149,740	149,740	149,740	149,740	149,740	149,740	0%	3%	2%	
Provisions	12,632	26,339	26,339	26,339	26,339	26,339	26,339	26,339	0%	0%	0%	
Debt securities issued at amortised cost	445,226	347,132	361,539	379,494	399,150	423,833	444,988	467,636	5%	6%	7%	see BCTT details
Other non-current liabilities	10,108	5,342	5,342	5,342	5,342	5,342	5,342	5,342	0%	0%	0%	
Total non-current liabilities	789,422	689,633	738,859	789,001	825,690	871,030	899,799	922,130	4%	13%	13%	
Accounts payable	525,212	373,961	385,753	457,169	522,463	536,569	560,346	573,139	6%	7%	8%	see NWC Schedule
Banking clients' deposits and other loans	2,245,330	3,090,963	3,844,039	4,005,619	4,182,499	4,404,619	4,594,991	4,798,791	5%	69%	67%	see BCTT details
Employee benefits	22,092	22,049	24,119	25,568	26,865	27,733	28,672	29,517	4%	0%	0%	
Short term debt	59,757	107,935	70,526	82,114	88,246	95,682	98,423	98,310	5%	1%	1%	see Debt Schedule
Financial liabilities at fair value through profit or	26,345	13,744	10,680	11,210	11,791	12,520	13,145	13,814	5%	0%	0%	
Debt securities issued at amortised cost	352	243	254	266	280	297	312	328	5%	0%	0%	
Other current liabilities	117,839	157,101	157,101	157,101	157,101	157,101	157,101	157,101	0%	3%	2%	
Other banking financial liabilities	46,211	47,760	83,155	83,155	83,155	83,155	83,155	83,155	0%	1%	1%	
Total current liabilities	3,043,136	3,813,756	4,575,626	4,822,202	5,072,399	5,317,677	5,536,145	5,754,155	5%	82%	81%	
Total liabilities	**3,832,559**	**4,503,389**	**5,314,485**	**5,611,204**	**5,898,089**	**6,188,707**	**6,435,944**	**6,676,285**	**4%**	**95%**	**94%**	
Total equity and liabilities	**4,057,488**	**4,756,642**	**5,609,557**	**5,932,710**	**6,248,977**	**6,574,752**	**6,858,053**	**7,123,096**	**5%**	**100%**	**100%**	

Consolidated Cash Flow Statement (excl. BCTT) (€k)	2022	2023	2024E	2025F	2026F	2027F	2028F	2029F	CAGR 25-29	2024E % CFO	2029F % CFO	Notes
Collections from customers	822,216	861,167	895,414	1,043,781	1,167,760	1,228,294	1,294,300	1,345,944	7%			
Payments to suppliers	(442,640)	(432,066)	(412,506)	(508,849)	(603,329)	(639,283)	(689,370)	(727,932)	9%			
Payments to employees	(333,526)	(361,412)	(395,394)	(419,146)	(440,414)	(454,639)	(470,030)	(483,883)	4%			
Other changes (BCTT)	(119,174)	1,037,181	-	-	-	-	-	-				
Cash flow generated by operations	(73,125)	1,104,871	87,514	115,785	124,017	134,373	134,899	134,128	4%			
Payments/receivables of income taxes	(16,360)	(1,583)	(17,071)	(20,527)	(22,273)	(24,922)	(24,931)	(23,800)	4%			
Other receivables/payments	249,494	(96,516)	1,465	63,544	57,101	6,488	15,932	8,115	-40%			
Cash flow from operating activities	**160,009**	**1,006,772**	**71,909**	**158,802**	**158,845**	**115,939**	**125,900**	**118,443**	**-7%**	**100%**	**100%**	
Tangible fixed assets	(16,059)	(14,833)	(16,909)	(17,018)	(18,121)	(20,171)	(17,148)	(16,763)	0%	24%	14%	
Intangible assets	(17,822)	(16,008)	(17,941)	(17,941)	(17,941)	(17,941)	(17,941)	(17,941)	0%	25%	15%	
Other changes (BCTT)	(653,505)	(983,926)	-	-	-	-	-	-		0%	0%	
Cash flow from investing activities	**(687,386)**	**(1,014,767)**	**(34,850)**	**(34,959)**	**(36,062)**	**(38,112)**	**(35,089)**	**(34,704)**	**0%**	**48%**	**29%**	
Net Loans	(15,761)	77,793	(5,276)	33,989	34,067	22,752	26,004	22,180	-10%	7%	-19%	
Interest expenses	(433)	(2,558)	(12,638)	(13,951)	(14,996)	(15,740)	(16,809)	(17,685)	6%	18%	15%	see Debt Schedule
Finance leases	(33,708)	(37,046)	(31,323)	(32,190)	(32,922)	(33,438)	(33,384)	(32,651)	0%	44%	28%	
Acquisition of own shares	(21,574)	(10,154)	(13,763)	(10,000)	(10,000)	(10,000)	(10,000)	(10,000)	0%	19%	8%	see Equity Appendix
Dividends	(17,656)	(17,888)	(23,316)	(21,021)	(23,167)	(24,967)	(24,225)	(23,732)	3%	32%	20%	
Other changes (BCTT)	170,352	(97,723)	-	-	-	-	-	-		0%	0%	
Cash flow from financing activities	**81,218**	**(87,575)**	**(86,316)**	**(43,173)**	**(47,018)**	**(61,392)**	**(58,414)**	**(61,888)**	**9%**	**120%**	**52%**	
Net Change in Cash (1+2+3)	(446,159)	(95,570)	(49,258)	45,670	75,765	16,434	32,397	21,851	-17%	69%	18%	
Cash at the beginning of the period	856,958	410,799	351,610	302,352	348,022	423,787	440,222	472,619	12%			
Cash at the end of the period	410,799	315,229	302,352	348,022	423,787	440,222	472,619	494,470	9%			
Other changes (BCTT)	45,670	36,380	-	-	-	-	-	-				
Cash and Cash Equivalent	**456,469**	**351,610**	**302,352**	**348,022**	**423,787**	**440,222**	**472,619**	**494,470**	**9%**			
(+) Cash from BCTT BS			78,607	80,368	82,295	84,716	86,790	89,011	3%	109%	75%	
Cash and Cash Equivalent (BS)	**456,469**	**351,610**	**380,959**	**428,390**	**506,083**	**524,938**	**559,409**	**583,482**	**8%**	**530%**	**493%**	

Appendix C2 – Notes to the Consolidated Financial Statements:

Asset Schedule	2022	2023	2024E	2025F	2026F	2027F	2028F	2029F
Tangible Fixed assets (beg. of the year)	296,288	303,206	296,995	331,712	323,332	302,747	291,636	284,693
CAPEX (Tangible)	16,696	17,696	16,909	17,018	18,121	20,171	17,148	16,763
New Contracts (RoU)	32,163	13,627	61,412	27,982	19,578	29,578	39,578	39,578
Depreciation	48,608	52,157	48,165	55,260	58,700	61,330	64,202	65,867
Terminated contracts (RoU)	-	1,668	194	-	-	6,995	28,653	28,610
Tangible Fixed assets YE	**303,206**	**296,995**	**331,712**	**323,332**	**302,747**	**291,636**	**284,693**	**275,770**
Intangible Fixed assets (beg. of the year)	63,507	69,409	70,640	71,347	70,599	68,788	65,553	60,894
CAPEX (Intangible)	20,298	18,400	17,941	17,941	17,941	17,941	17,941	17,941
Amortization	16,266	17,034	17,234	18,689	19,752	21,176	22,600	24,024
Intangible Fixed assets YE	**69,409**	**70,640**	**71,347**	**70,599**	**68,788**	**65,553**	**60,894**	**54,811**

NWC Schedule	2022	2023	2024E	2025F	2026F	2027F	2028F	2029F
Inventories	8,041	6,663	11,171	13,649	16,081	17,026	18,330	19,328
Days	*10*	*8*	*12*	*12*	*12*	*12*	*12*	*12*
Accounts receivable	147,131	153,062	163,388	171,260	179,453	187,071	194,917	199,595
Days	*59*	*57*	*57*	*57*	*57*	*57*	*57*	*57*
Accounts payable	525,212	373,961	385,753	457,169	522,463	536,569	560,346	573,139
Days	*658*	*442*	*428*	*416*	*403*	*391*	*379*	*368*

Debt Schedule	2022	2023	2024E	2025F	2026F	2027F	2028F	2029F
Total Debt	**195,955**	**269,015**	**248,518**	**274,686**	**288,476**	**299,769**	**322,790**	**340,747**
ST	59,757	107,935	70,526	82,114	88,246	95,682	98,423	98,310
% ot Total Debt	*30%*	*40%*	*28%*	*30%*	*31%*	*32%*	*30%*	*29%*
Medium and LT	136,198	161,080	195,899	228,086	245,118	265,775	273,389	273,073
% ot Total Debt	*70%*	*60%*	*79%*	*83%*	*85%*	*89%*	*85%*	*80%*
Total Debt to EBITDA	1.57	1.87	1.87	1.87	1.87	1.87	1.87	1.87
of which Lease Liabilities	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	2022	2023	2024E	2025F	2026F	2027F	2028F	2029F
Retained Earnings (beg. of the Year)	43,904	64,647	83,269	119,951	145,643	172,838	202,147	238,484
(+) Net Profit (previous Year)	38,404	36,407	60,511	46,712	50,362	54,276	60,562	59,331
(-) Dividends	(17,656)	(17,888)	(23,316)	(21,021)	(23,167)	(24,967)	(24,225)	(23,732)
Payout Ratio	46%	49%	39%	45%	46%	46%	40%	40%
Retained Earnings YE	64,647	83,269	119,951	145,643	172,838	202,147	238,484	274,083

Appendix C3 – Income Statement Assumptions & Drivers:

Mail Income Statement	Unit	2024E	2025F	2026F	2027F	2028F	2029F	Notes for Assumptions	CAGR 25-29
Revenues	**€k**	**440,294**	**435,589**	**444,595**	**443,811**	**442,232**	**440,680**	**Sum of Addressed Mail and Business Solutions & Other**	**0.3%**
Addressed Mail	**€k**	**375,249**	**370,593**	**379,472**	**378,875**	**377,467**	**376,063**	The revenue from Addressed Mail was determined using mail volume data provided by ANACOM for the period from Q1 2005 to Q2 2024. Future volumes were projected up to Q4 2029 using a SARIMA statistical model. Quarterly volumes were aggregated into annual totals, and revenues were calculated using a pricing formula outlined in the agreement with ANACOM. This agreement, tied to CTT's role as a USO provider, is scheduled to expire at the end of FY2028 but is assumed to be renewed under the same terms for a new future concession period. The pricing formula incorporates several factors, including macroeconomic indicators (such as the inflation CPI index provided by INE, calculated on a June-to-June basis), other fixed variables reflecting CTT's sustained costs, and the decline in Addressed Mail volumes (excluding bulk mail). Prices were adjusted yearly to account for the year-over-year price variation derived from the formula.	0.4%
Addressed Mail Volumes	items (M)	420,587	390,924	362,901	336,887	312,738	290,320		
Pricing Convention Formula									
CPI	%	2.5%	1.9%	1.8%	1.8%	1.8%	1.8%		
Δ Volumes	%	-8.4%	-7.1%	-7.2%	-7.2%	-7.2%	-7.2%		
VC (Variable Costs factor)	%	16.0%	16.0%	16.0%	16.0%	16.0%	16.0%		
E (Efficiency Factor)	%	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%		
K (Extraodinary Conditions)	%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%		
Δ Price YoY	%	11.5%	6.3%	10.3%	7.6%	7.3%	7.3%		
Price	€	0.97	1.03	1.14	1.23	1.32	1.41		
Business Solutions & Other	**€k**	**65,044**	**64,996**	**65,123**	**64,935**	**64,765**	**64,616**	Miscellaneous assumptions were based on historical growth, aggregating revenues from Business Solutions, Retail, Parcels (USO), Philately, and other sources.	-0.1%
Operating Costs	**€k**	**405,927**	**406,432**	**415,269**	**422,299**	**429,324**	**436,170**	Operating costs are expected to increase due to the service quality requirements of the USO concession obligations, with margins projected to decline, leading to continued unprofitability for the segment, as seen in recent years. ES&S costs are anticipated to stabilize at 19% of sales, consistent with historical trends, while staff costs are projected to grow at an estimated 2% (CTT estimates a 2.5%).	**1.8%**
External Supplies and Services	€k	82,956	82,070	83,767	83,619	83,321	83,029		0.3%
Staff Costs	€k	315,083	321,385	327,812	334,369	341,056	347,877		2.0%
Other Operating Costs	€k	7,888	2,977	3,690	4,311	4,947	5,264		15.3%
EBITDA	**€k**	**34,366**	**29,157**	**29,325**	**21,512**	**12,907**	**4,510**		**-37.3%**
Depreciation & Amortization	€k	37,761	35,691	33,735	31,887	30,139	28,487	Depreciation and Amortization (D&A) Expenses are derived from a reallocation of D&A calculated in the Asset Schedule, based on assets attributed to the Mail segment. These expenses are expected to decline over time due to asset utilization.	-5.5%
EBIT	**€k**	**(3,394)**	**(6,534)**	**(4,410)**	**(10,375)**	**(17,232)**	**(23,977)**	A negative EBIT is expected for the upcoming years	**38.4%**

E&P Income Statement (Acquisitions)	Unit	2024E	2025F	2026F	2027F	2028F	2029F	Notes for Assumptions	CAGR 25-29
Industry Indicators									
Portugal									
Retail Sales	€B	58.84	60.03	61.25	62.43	63.71	64.77	These variables were used as proxies for e-commerce trends, with data sourced from Euromonitor forecasts for Portugal and Spain through FY28. E-commerce Retail Sales are expected to grow significantly in the coming years, outpacing the overall Retail Sales CAGR due to digitalization. For FY29, the team anticipates a more moderate YoY growth of 5%, reflecting the typical deceleration seen in mature EU markets. Historical CEP data, provided by ANACOM for Portugal and CNMC for Spain—the national regulators for communication and postal services—was also analyzed and projected, maintaining the same proportion relative to overall E-commerce Retail Sales. Additionally, a breakdown of transportation into International (Inbound and Outbound) and National segments was included to offer a clearer understanding of CTT's market shares. The team expects these proportions to remain consistent with FY23 levels, adopting a conservative approach due to the ongoing uncertainty surrounding International Inbound Volumes caused by geopolitical tensions.	1.9%
E-commerce Retail Sales	€B	4.56	4.89	5.32	5.82	6.39	6.71		8.2%
CEP Sales	€B	0.54	0.58	0.63	0.69	0.76	0.79		8.2%
CEP International	€B	0.29	0.31	0.33	0.36	0.40	0.42		8.2%
CEP National	€B	0.25	0.27	0.30	0.32	0.36	0.37		8.2%
Spain									
Retail Sales	€B	257.52	261.47	266.10	270.49	274.85	278.55		1.6%
E-commerce Retail Sales	€B	31.17	33.89	36.98	40.23	43.61	45.79		7.8%
CEP Sales	€B	6.59	7.17	7.82	8.51	9.22	9.68		7.8%
CEP International	€B	2.30	2.51	2.73	2.97	3.22	3.39		7.8%
CEP National	€B	4.29	4.66	5.09	5.53	6.00	6.30		7.8%
Revenue Breakdown									
Revenues	**€k**	**426,076**	**557,965**	**675,924**	**739,908**	**809,821**	**864,802**	**Sum of Portugal, Spain and Other Revenues**	**11.6%**
Portugal	**€k**	**154,441**	**180,227**	**228,432**	**248,234**	**270,495**	**285,486**	**Sum of Parcels, Cargo, Banking Network, Logistics and Other**	**12.2%**
Parcels	€k	141,140	166,888	214,938	234,500	256,457	271,053	Parcels Revenue from Portugal is expected to grow in line with E-commerce Retail Sales PT, with market share projected to increase through the DHL joint venture. This includes both International and National inflows for DHL Parcel Portugal, resulting in a significant market share boost of c.10% for International flows and c.6% for National flows comparing to a stand-alone scenario.	12.9%
International	€k	14,197	25,222	49,090	53,010	57,238	61,872		25.2%
Market Share	%	5%	8%	15%	15%	14%	15%		
National	€k	126,944	141,666	165,848	181,490	199,219	209,180		10.2%
Market Share	%	50%	52%	56%	56%	56%	56%		
Cargo	€k	3,555	3,200	2,880	2,592	2,332	2,099	Cargo is a declining business, and CTT is struggling to attract new clients	-10.0%
Banking network	€k	4,324	4,290	4,293	4,302	4,295	4,297	Relatively stable Revenues deriving from the Banking Network (moving avg 3yrs)	0.0%
Logistics	€k	4,285	4,713	5,184	5,703	6,273	6,900	CTT is shifting from being a pure last-mile provider to an end-to-end orchestrator of the cross-border shipping chain, with the partnership expected to boost this source of Revenue	10.0%
Other	€k	1,137	1,137	1,137	1,137	1,137	1,137	constant	0.0%
Spain	**€k**	**267,411**	**355,429**	**416,190**	**457,047**	**500,837**	**536,361**	**Sum of Parcels, Cargo and Logistics**	**10.8%**
Parcels	€k	267,411	303,001	336,310	365,679	396,322	416,799	Parcels Revenue from Spain is expected to grow, in line with E-commerce Retail Sales ES, with market share projected to increase through the Cacesa acquisition on International Flows by c.0.7%	8.3%
International	€k	10,177	23,276	31,045	33,620	36,361	38,840		13.7%
Market Share	%	0.4%	0.9%	1.1%	1.1%	1.1%	1.1%		
National	€k	257,234	279,724	305,265	332,058	359,961	377,959		7.8%
Market Share	%	6%	6%	6%	6%	6%	6%		
Cargo	€k	-	16,406	24,696	27,906	31,534	35,633	This line represents Cacesa's Air Freight business. The impact on CAGR is primarily due to the acquisition, expected to close in March 2025; only the revenue from Cacesa after this date is included. A CAGR of 13% was estimated for Cacesa's stand-alone business, driven by a positive industry outlook.	21.4%
Logistics	€k	-	36,023	55,184	63,462	72,981	83,928	This line represents Cacesa's Customs Clearance business. The impact on CAGR is primarily due to the acquisition, expected to close in March 2025; only the revenue from Cacesa after this date is included. A CAGR of 15% was estimated for Cacesa's stand-alone business, driven by a positive industry outlook.	23.5%
Others	**€k**	**4,225**	**22,309**	**31,302**	**34,628**	**38,489**	**42,955**	**Cacesa already has operations around EU, mainly Italy, Belgium and Poland**	**17.8%**
Operating Costs	**€k**	**379,029**	**490,436**	**597,836**	**641,383**	**700,278**	**745,795**	**Sum of ES&S, Staff Costs and Other Operating Costs**	**11.0%**
External Supplies and Services	€k	328,038	424,076	517,032	553,284	603,823	642,755	A decline is expected on a stand-alone basis, driven by efficiency gains from automation, offset by an initial impact of dyssynergies from the acquisitions (+100bps) and a positive effect from FY26 onwards due to future synergies (-167bps). The synergy estimates are based on the figures presented in the Acquisition and Partnership Statements released in December 18 and December 19.	11.0%
% on Sales	%	77%	76%	76%	75%	75%	74%		
Staff Costs	€k	49,958	65,819	80,143	87,327	95,570	102,078	Staff Costs are expected to be aligned with Revenue Growth	11.6%
% on Sales	%	12%	12%	12%	12%	12%	12%		
Other Operating Costs	€k	1,033	541	661	772	885	962	Miscellaneous Assumptions, level consistent with recurring items	15.5%
EBITDA	**€k**	**47,047**	**67,529**	**78,088**	**98,525**	**109,543**	**119,007**		**15.2%**
D&A	€k	14,959	14,440	13,898	13,228	12,606	12,031	Depreciation and Amortization (D&A) Expenses are derived from a reallocation of D&A calculated in the Asset Schedule, based on assets attributed to the E&P segment. These expenses are expected to lower thanks to the recent investments and renewal in Fixed Assets	-4.5%
EBIT	**€k**	**32,088**	**53,090**	**64,190**	**85,297**	**96,937**	**106,975**		**19.1%**

Appendix C4 – Investment Risks – Other Risks:

MR 1 | Market Risk | Interest Rate

Banco CTT's profitability is influenced by fluctuations in interest rates, which directly impact net interest margins. Rising interest rates can increase borrowing costs, potentially reducing loan demand, while also driving up the cost of deposits. Although Banco CTT employs fixed rates in its auto loan segment to partially 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. Moreover, the attractiveness of savings certificates is heavily dependent on interest rate changes. When interest rates are higher, investors might look for more appealing alternative investments, such as bank deposits, leading to a decrease in demand for saving certificates. Series F saving certificate rates are linked to the Euribor 3M rate and subjected to a floor of 0% and a cap of 2.5%, limiting its competitiveness in a scenario of increasing interest rates.

MR 2 | Market Risk | Macroeconomic Factors

Macroeconomic changes like economic downturns, inflation, and political instability in Portugal and other regions could adversely impact CTT's performance. The bank monitors macroeconomic conditions and limits its exposure to market risks by managing its own portfolio against predefined risk tolerance levels. These measures are reviewed by the Board of Directors and related committees to ensure alignment with strategic objectives. Negative macroeconomic changes can have a high impact on consumption.

MR 3 | Market Risk | Competition

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

CTT also faces competition within the Financial Services BU. Regarding the distribution of savings certificates, the company is not the only underwriter of these certificates and as of the beginning of 2024, Banco BIG also started distributing these certificates. Even considering that little to no effects were reflected in CTT's results thus far, this might present a threat in the long run if market liberalization leads to additional players. Moreover, by selling insurance products from Generali, CTT is also competing with other insurers which is a considerably more competitive market.

MR 4 | Market Risk | Credit Risk

Banco CTT's exposure to credit risk arises from its loan portfolio, which could be affected by multiple different factors. The bank addresses this risk through a credit risk assessment methodology that evaluates customers' repayment capacity and defines credit limits. Risk is further mitigated through sector diversification, focusing on mortgage and auto loans, as well as securitization strategies for auto loans to transfer possible risks.

MR 5 | Market Risk | Urbanization

CTT has a strong presence in the rural areas however around 68.6% of the Portuguese population lives in the urban area and it is expected to keep increasing to 75.3% by 2040. The urbanization of the population might lead to a decrease in demand for other traditional financial services (such as money orders, payments, and retail), which might be more sought after in the rural regions. Mitigation: CTT is looking into modernizing its services to align with urbanization trends through self-service lockers as well as the enhancement of 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 1 | Operational Risk

Operational risks arise from shortcomings or failures in internal processes, systems, human actions, or external events. These risks can significantly disrupt daily operations. Common examples include system outages, inefficiencies in processes, or errors in service delivery, all of which have the potential to impact CTT negatively. These risks are managed through a comprehensive framework integrating risk identification, assessment, and mitigation across all functional units, ensuring compliance with the Internal Control System.

OR 2 | Operational Risk | Cost Savings

Cost control, particularly in the Mail BU, is a fundamental aspect of coping with its relentless volume decline. It is challenging to cut costs without compromising the service quality standards that are imposed by ANACOM. The level of inflation and labor costs are crucial drivers in this challenge. Moreover, the current USO quality standards, updated by ANACOM at the end of 2023 and effective from January 1, 2025, are still above the EU average, burdening CTT with extra effort in terms of operation and hence costs. A prolonged misalignment in this sense would be a further challenge to the cost control strategy.

RR | Reputational Risk

Reputation is an important factor of trust in CTT's operating sectors, with risks arising from compliance breaches, operational failures, or negative publicity. Such events can destroy confidence, leading to a loss of customers and potential liquidity pressures. To mitigate this risk, CTT reinforces its Code of Conduct through regular training. Over 4,200 employees participated in anti-corruption training, and 903 employees received targeted instruction on anti-money laundering and counter-terrorism financing. These measures aim to enhance ethical awareness and protect CTT's reputation from the inside.

TCR | Technology & Cybersecurity Risk

As reliance on digital services grows, CTT is increasingly exposed to cybersecurity threats, such as data breaches and operational disruptions. To mitigate these risks, CTT has implemented security controls, policies, and governance structures. It conducts employee training on best practices for telework and raises awareness about cybercrime. Additionally, the Information Security Forum continuously monitors risk exposure and oversees strategic and tactical initiatives to strengthen the overall cybersecurity posture.

LR | Liquidity Risk

Liquidity risk for CTT encompasses the possibility of significant losses arising from a deterioration in financing conditions and the forced sale of assets. CTT actively manages this risk by setting liquidity risk limits, complying with regulatory standards, and monitoring exposure through key risk indicators at least quarterly. However, external shocks and unexpected market conditions could still challenge CTT's ability to maintain adequate liquidity.

ER | ESG Risk

The attention to ESG factors from the customers is substantial. Being able to operate the transition toward a sustainable fleet of vehicles as virtuously as the competitors is crucial. The Iberian e-sellers (70.7% PT, 95% ES) claim they are including the environmental theme in their selling strategy, even if it implies higher delivery costs. CTT has ca. 14% of EVs in its fleet as of 2023.

PRL 2 | Political, Regulatory, and Legal Risk | Government Intervention

CTT is subjected to changes in government policy such as limitations on subscription conditions. The potential impact of such interventions can greatly affect the sale of savings certificates, as was previously shown by a change of -87.2% in revenues in savings from 1H2023 to 1H2024. These results were registered posterior to the government announcement of the reduction of subscription of series F certificates to €50k per subscriber in June 2023. The diversified portfolio of CTT offsets this risk partially, especially considering the ability to partially relocate these funds to the Banco CTT.

PRL 3 | Political, Regulatory and Legal Risk | Compliance and Legal

Operating in a regulated environment, Banco CTT must ensure compliance with anti-money laundering and data protection regulations, including GDPR. Failure to comply could result in severe penalties and reputational damage. To mitigate these risks, the bank employs an integrated risk management system, and a governance model structured around the "three lines of defense" framework. This system involves active participation from top management to operational levels, establishing internal controls and adherence to regulatory requirements.

Appendix C5 – Financial Analysis:

Efficiency Ratios	FY19	FY20	FY21	FY22	FY23	2024E	2025F	2026F	2027F	2028F	2029F	Industry
Fixed Assets Turnover (x)	2.81x	2.53x	2.86x	2.99x	3.32x	3.05x	3.58x	4.26x	4.65x	5.01x	5.37x	7.09x
A/R (Days)	72	75	69	59	57	57	57	57	57	57	57	65
A/P (Days)	790	714	496	658	442	428	416	403	391	379	368	414
Inventory (Days)	12	13	10	10	8	12	12	12	12	12	12	13
Cash Conversion Cycle (CCC)	-706	-626	-417	-589	-377	-359	-346	-334	-322	-310	-299	-336

Solvency Ratios	FY19	FY20	FY21	FY22	FY23	2024E	2025F	2026F	2027F	2028F	2029F	Industry
Debt to Equity Ratio (%)	133%	138%	115%	87%	106.22%	90%	96%	95%	94%	88%	83%	124%
Long and short-term Debt Ratio (%)	7%	7%	6%	5%	6%	5%	5%	5%	5%	5%	5%	34%
Long-term Debt Ratio (%)	6%	6%	4%	3%	3%	3%	4%	4%	4%	4%	4%	20%
Equity Multiplier (x)	19.13x	19.26x	20.54x	18.04x	18.78x	19.01x	18.45x	17.81x	17.03x	16.25x	15.94x	7.30x
Liabilities to Equity Ratio	18.13x	18.26x	19.54x	17.04x	17.78x	18.01x	17.45x	16.81x	16.03x	15.25x	14.94x	2.69x
Debt to EBITDA	2.76x	2.14x	1.68x	1.57x	1.87x	1.87x	1.87x	1.87x	1.87x	1.87x	1.87x	3.64x
Interest Coverage Ratio (x)	4.54x	3.57x	7.25x	6.06x	4.61x	6.10x	6.59x	6.66x	7.04x	6.66x	6.15x	15.47x

Liquidity Ratios	FY19	FY20	FY21	FY22	FY23	2024E	2025F	2026F	2027F	2028F	2029F	Industry
Current Ratio (x)	0.42x	0.40x	0.60x	0.59x	0.63x	0.69x	0.69x	0.70x	0.71x	0.72x	0.72x	1.03x
Cash Ratio (x)	0.24x	0.23x	0.32x	0.15x	0.09x	0.08x	0.09x	0.10x	0.10x	0.10x	0.10x	0.27x
Quick Ratio (x)	0.32x	0.30x	0.38x	0.20x	0.13x	0.12x	0.12x	0.14x	0.13x	0.14x	0.14x	0.97x

Profitability Ratios	FY19	FY20	FY21	FY22	FY23	2024E	2025F	2026F	2027F	2028F	2029F	Industry
EBITDA Margin (%)	9%	13%	14%	14%	15%	14%	14%	14%	14%	14%	13%	13%
EBIT Margin (%)	6%	5%	7%	6%	8%	8%	8%	8%	8%	8%	7%	7%
Net Profit Margin (%)	4%	2%	5%	4%	6%	5%	5%	5%	5%	5%	5%	4%
OCF/Sales (%)	19%	12%	8%	31%	-3%	7%	14%	12%	9%	9%	8%	10%
ROA (%)	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	4%
ROIC (%)	**10%**	**5%**	**10%**	**9%**	**12%**	**8%**	**9%**	**9%**	**9%**	**9%**	**8%**	**13%**
ROE (%)	**22%**	**11%**	**22%**	**16%**	**24%**	**18%**	**18%**	**18%**	**18%**	**16%**	**15%**	**21%**

Value Creation and CashFlows Ratios	FY19	FY20	FY21	FY22	FY23	FY24	FY25	FY26	FY27	FY28	FY29
Cash to Income	6.47	8.20	0.86	2.85	12.94	0.93	1.73	1.59	1.05	1.12	1.09

Appendix C6 – 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	**678,855**	**0.62**	**0.75**	**Postal Service**	**14.64**	**27%**	**0.06**	**16%**
Malta Post	39,025	0.60	0.73	Postal Service	0.06	30%	0.70	16%
Bpost	404,877	0.91	0.94	Couriers and Messengers	1.26	25%	0.48	64%
PostNL	535,618	0.91	0.94	Postal Service	4.94	26%	0.20	44%
Oesterreichische Post	2,012,309	0.29	0.53	Postal Service	5.30	23%	0.10	3%
Logista	4,015,723	0.58	0.72	Professional, Scientific, and Technical Services	0.44	25%	0.54	5%
InPost	8,538,044	1.02	1.01	Couriers and Messengers	5.13	25%	0.21	2%
DHL	42,430,091	1.03	1.02	Postal Service	0.99	30%	0.60	5%

Industry	Average Cash Holdings to EV	CTT's β Unlevered Cash Adj. by segment	CTT's β Levered by segment
Mail	17%	0.49	0.86
E&P	24%	0.54	0.96

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.

Mail FCFE	Unit	2025F	2026F	2027F	2028F	2029F	TV
NOPAT	€k	-6,534	-4,410	-10,375	-17,232	-23,977	
(+) 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	4,858	2,116	3,373	3,325	1,957	
(-) Interest Expense * (1-T)	€k	6,110	6,568	6,894	7,362	7,746	
(+) Net Borrowings	€k	20,096	20,428	20,157	14,012	10,637	
FCFE	€k	1,868	-1,672	-3,673	-2,166	-6,229	-73,816
PV(FCFE)	€k	1,868	-1,542	-3,123	-1,698	-4,504	-53,374
Equity Value	**€k**	**-62,373**					

E&P FCFE	Unit	2025F	2026F	2027F	2028F	2029F	TV
NOPAT	€k	38,220	44,573	51,523	59,030	64,522	
(+) 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	-2,395	-3,137	-3,792	-3,930	-2,346	
(-) Interest Expense * (1-T)	€k	4,151	4,462	4,683	5,001	5,262	
(+) Net Borrowings	€k	9,904	10,289	10,279	15,666	19,244	
FCFE	€k	31,899	33,357	41,029	44,671	42,775	542,263
PV(FCFE)	€k	31,899	30,415	34,112	33,857	29,561	374,751
Equity Value	€k	534,596					
Equity Value (CTT 75% stake)	**€k**	**534,596**					

FS FCFE	Unit	2025F	2026F	2027F	2028F	2029F	TV
NOPAT	€k	17,448	16,499	15,625	15,020	14,266	
(+) D&A	€k	122	115	109	103	97	
(-) CapEx	€k	161	158	156	154	154	
(-) Δ NWC	€k	-3,708	964	802	691	450	
(-) Interest Expense * (1-T)	€k	0	0	0	0	0	
(+) Net Borrowings	€k	0	0	0	0	0	
FCFE	€k	21,117	15,492	14,776	14,277	13,759	163,353
PV(FCFE)	€k	21,117	14,147	12,322	10,869	9,566	113,566
Equity Value	**€k**	**181,586**					

BCTT FCFE	Unit	2025F	2026F	2027F	2028F	2029F	TV
Net Income	€k	10,800	11,783	13,103	14,393	13,067	
FCFE	€k	10,800	11,783	13,103	14,393	13,067	151,532
PV(FCFE)	€k	10,800	10,651	10,707	10,629	8,723	101,158
Equity Value	€k	152,669					
Equity Value (CTT 91.29% stake)	**€k**	**139,372**					

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 C7 – Alternative Valuation Methods:

Identifier (RIC)	Company Name	Industry	EV / EBITDA	P / E
BPOST.BR	Bpost SA	Couriers and Messengers	5.04	6.27
INPST.AS	InPost SA	Couriers and Messengers	12.99	36.24
PST.MI	Poste Italiane SpA	Credit Intermediation and Related Activities	16.69	8.21
PTNL.AS	PostNL NV	Postal Service	4.67	34.06
DHLn.DE	Deutsche Post AG	Postal Service	6.91	14.61
POST.VI	Oesterreichische Post AG	Postal Service	6.59	13.98
MTPT.MT	MaltaPost plc	Postal Service	4.57	13.15
LOG.MC	Logista Integral SA	Professional, Scientific, and Technical Services	6.77	11.58
Mean			**8.03**	**17.26**
Median			6.68	13.57

CTT data	
EBITDA (LTM)	146.30
EPS (LTM)	0.38
Debt (9M24)	232.74
Cash (9M24)	53.31
Number of Shares	137.47

	Equity Value (€M)	
Group	**999.59**	**910.38**

Value per Share		
FCFE	EV / EBITDA	P / E
€ 7.16	€ 7.27	€ 6.62

Identifier (RIC)	Company Name	Industry	EV / EBITDA
BPOST.BR	Bpost SA	Couriers and Messengers	5.04
INPST.AS	InPost SA	Couriers and Messengers	12.99
PTNL.AS	PostNL NV	Postal Service	4.67
DHLn.DE	Deutsche Post AG	Postal Service	6.91
POST.VI	Oesterreichische Post AG	Postal Service	6.59
MTPT.MT	MaltaPost plc	Postal Service	4.57
LOG.MC	Logista Integral SA	Professional, Scientific, and Technical Services	6.77
Mean			**6.79**
Median			6.59

CTT data	
EBITDA (LTM)	80.49
Debt (9M24)	232.74
Cash (9M24)	53.31
Number of Shares	137.47

	Equity Value (€M)
Logistics	**366.97**

Value per Share	
FCFE	EV / EBITDA
€ 3.48	€ 3.01

The selection of peers for both the CTT group and the Logistics-only segment was based on a qualitative screening of the *Courier, Postal, Air Freight & Land-based Logistics* industry classification provided by Refinitiv. The primary objective was to ensure the highest possible level of comparability within the peer group, despite the inherent complexity of CTT's operating environment. Consequently, the peer group primarily consists of European postal operators, although some differences in business diversification persist, as previously discussed in the report.

Appendix C8 – Sensitivity Analysis:

Mail Sensitivity Analysis

		Cost of Equity						
	- 62 €	7.7%	7.9%	8.2%	8.4%	8.7%	8.9%	9.2%
Perpetuity Growth Rate	0.3%	-67	-65	-62	-60	-58	-57	-55
	0.2%	-68	-65	-63	-61	-59	-57	-55
	0.1%	-69	-66	-64	-62	-60	-58	-56
	0.0%	-69	-67	-65	-62	-60	-58	-56
	-0.1%	-69	-66	-64	-62	-60	-58	-56
	-0.2%	-68	-66	-63	-61	-59	-57	-56
	-0.3%	-67	-65	-63	-61	-59	-57	-55
		8%	8%	8%	8%	9%	9%	9%
	0.3%	0.04	0.05	0.05	0.05	0.05	0.06	0.06
	0.2%	0.04	0.05	0.05	0.05	0.05	0.06	0.06
	0.1%	0.04	0.05	0.05	0.05	0.05	0.05	0.06
	0.0%	0.04	0.04	0.05	0.05	0.05	0.05	0.06
	-0.1%	0.04	0.05	0.05	0.05	0.05	0.05	0.06
	-0.2%	0.04	0.05	0.05	0.05	0.05	0.05	0.06
	-0.3%	0.04	0.05	0.05	0.05	0.05	0.06	0.06

Mail Sensitivity Analysis

		Yearly Increase in Staff Cost						
	- 62 €	2.5%	2.3%	2.2%	2.0%	1.9%	1.7%	1.6%
"+/- additional changes in Volumes"	0.3%	-86	-61	-35	-10	15	40	64
	0.2%	-104	-78	-53	-28	-3	22	47
	0.1%	-121	-96	-70	-45	-20	5	30
	0.0%	-139	-113	-88	-62	-37	-12	12
	-0.1%	-156	-130	-105	-80	-55	-30	-5
	-0.2%	-173	-147	-122	-97	-72	-47	-22
	-0.3%	-190	-164	-139	-114	-89	-64	-39
		2%	2%	2%	2%	2%	2%	2%
	0.3%	0.02	0.05	0.08	0.11	0.13	0.16	0.19
	0.2%	0.00	0.03	0.06	0.09	0.11	0.14	0.17
	0.1%	-0.01	0.01	0.04	0.07	0.10	0.12	0.15
	0.0%	-0.03	-0.01	0.02	0.05	0.08	0.10	0.13
	-0.1%	-0.05	-0.02	0.00	0.03	0.06	0.08	0.11
	-0.2%	-0.07	-0.04	-0.01	0.01	0.04	0.07	0.09
	-0.3%	-0.09	-0.06	-0.03	-0.01	0.02	0.05	0.07

Express & Parcels Sensitivity Analysis

		Cost of Equity						
	845	11.2%	10.7%	10.2%	9.7%	9.2%	8.7%	8.2%
Perpetuity Growth Rate	2.3%	838	841	843	845	847	849	852
	2.2%	838	841	843	845	847	849	852
	2.1%	838	841	843	845	847	849	852
	2.0%	838	841	843	845	847	849	852
	1.9%	838	841	843	845	847	849	852
	1.8%	838	841	843	845	847	849	852
	1.7%	838	841	843	845	847	849	852
		11.2%	10.7%	10.2%	9.7%	9.2%	8.7%	8.2%
	2.3%	0.01	0.05	0.07	0.08	0.09	0.10	0.11
	2.2%	0.01	0.04	0.06	0.07	0.08	0.09	0.10
	2.1%	0.01	0.04	0.05	0.06	0.06	0.07	0.08
	2.0%	0.01	0.03	0.04	0.05	0.05	0.06	0.07
	1.9%	0.01	0.03	0.04	0.04	0.04	0.05	0.06
	1.8%	0.01	0.02	0.03	0.03	0.04	0.04	0.04
	1.7%	0.01	0.02	0.02	0.03	0.03	0.03	0.03

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.

Mail | The main sources of uncertainty are the changes in costs as the segment is already incurring high costs and is exposed to potential further increases by regulators, and the change in volumes of mail.

E&P | To better understand the robustness of this segment, we applied a stress test to the most relevant metrics in the forecasting process in both Portugal and Spain. The valuation of the segment does not shift too far from our computation, showing the strength of our forecast.

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

Note: Green values, buy recommendation; Blue values, Hold Recommendation; Red values, sell recommendation.

Express & Parcels Sensitivity Analysis

Parcels Volumes (% increase per year) × Prices (% Increase)

	-10%	-8%	-5%	-3%	0%	5%	10%	15%	20%
25%	1470	1510	1550	1590	1629	1709	1788	1868	1947
20%	1124	1155	1185	1215	1245	1306	1366	1426	1486
15%	893	917	941	965	989	1037	1084	1132	1179
10%	741	760	780	800	819	858	898	937	976
5%	640	657	674	691	707	741	775	808	842
0%	573	589	604	619	**634**	664	694	723	753
-5%	529	543	557	571	585	612	640	667	694
-10%	499	512	525	538	551	577	603	628	654
-15%	477	490	502	515	527	552	577	601	626
-20%	461	473	485	497	509	533	557	581	604
-25%	448	460	472	483	495	518	541	564	587

Parcels Volumes (% increase per year) × Prices (% Increase)

	-10%	-8%	-5%	-3%	0%	5%	10%	15%	20%
25%	13.39	13.69	13.98	14.27	14.57	15.15	15.74	16.33	16.91
20%	10.84	11.06	11.29	11.51	11.73	12.18	12.62	13.07	13.51
15%	9.14	9.31	9.49	9.67	9.84	10.19	10.54	10.89	11.24
10%	8.01	8.15	8.30	8.44	8.59	8.88	9.17	9.45	9.74
5%	7.27	7.39	7.51	7.64	7.76	8.01	8.26	8.51	8.75
0%	6.77	6.89	7.00	7.11	**7.22**	7.44	7.66	7.88	8.10
-5%	6.45	6.55	6.65	6.75	6.86	7.06	7.26	7.47	7.67
-10%	6.23	6.32	6.42	6.51	6.61	6.80	6.99	7.18	7.37
-15%	6.07	6.16	6.25	6.34	6.43	6.62	6.80	6.98	7.16
-20%	5.95	6.04	6.12	6.21	6.30	6.48	6.65	6.83	7.00
-25%	5.85	5.94	6.02	6.11	6.20	6.37	6.54	6.71	6.88

Parcels Volumes (% increase per year) × Prices (% Increase)

	-10%	-8%	-5%	-3%	0%	5%	10%	15%	20%
25%	96.4%	100.7%	105.0%	109.3%	113.6%	122.2%	130.8%	139.4%	148.0%
20%	58.9%	62.2%	65.5%	68.8%	72.0%	78.6%	85.1%	91.6%	98.1%
15%	34.0%	36.6%	39.1%	41.7%	44.3%	49.5%	54.6%	59.7%	64.9%
10%	17.4%	19.6%	21.7%	23.8%	25.9%	30.2%	34.4%	38.6%	42.9%
5%	6.5%	8.4%	10.2%	12.0%	13.8%	17.5%	21.1%	24.7%	28.3%
0%	-0.7%	1.0%	2.6%	4.2%	5.9%	9.1%	12.3%	15.6%	18.8%
-5%	-5.5%	-4.0%	-2.5%	-1.0%	0.5%	3.5%	6.5%	9.5%	12.4%
-10%	-8.7%	-7.3%	-5.9%	-4.5%	-3.1%	-0.3%	2.5%	5.3%	8.1%
-15%	-11.0%	-9.7%	-8.4%	-7.0%	-5.7%	-3.0%	-0.3%	2.3%	5.0%
-20%	-12.8%	-11.5%	-10.2%	-8.9%	-7.6%	-5.0%	-2.4%	0.1%	2.7%
-25%	-14.2%	-12.9%	-11.7%	-10.4%	-9.2%	-6.6%	-4.1%	-1.6%	0.8%

Parcels Volumes (% increase per year) × Prices (% Increase)

	-10%	-8%	-5%	-3%	0%	5%	10%	15%	20%
25%	96%	101%	105%	109%	114%	122%	131%	139%	148%
20%	59%	62%	65%	69%	72%	79%	85%	92%	98%
15%	34%	37%	39%	42%	44%	49%	55%	60%	65%
10%	17%	20%	22%	24%	26%	30%	34%	39%	43%
5%	7%	8%	10%	12%	14%	17%	21%	25%	28%
0%	-1%	1%	3%	4%	**6%**	9%	12%	16%	19%
-5%	-5%	-4%	-2%	-1%	1%	4%	6%	9%	12%
-10%	-9%	-7%	-6%	-4%	-3%	0%	3%	5%	8%
-15%	-11%	-10%	-8%	-7%	-6%	-3%	0%	2%	5%
-20%	-13%	-11%	-10%	-9%	-8%	-5%	-2%	0%	3%
-25%	-14%	-13%	-12%	-10%	-9%	-7%	-4%	-2%	1%

Given the critical importance of the E&P segment, an additional sensitivity analysis was performed on Volumes (x-axis) and Prices (y-axis). The Hold recommendation remains robust under these conditions. **Note:** on the axis, percentage increase of parcel revenue per item; percentage yearly increase in parcel volumes. Green values, buy recommendation; Blue values, Hold Recommendation; Red values, sell recommendation