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Explaining Narrow-Body aircraft depreciation and value dynamics with machine learning

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Abstract. Accurate forecasting of aircraft depreciation is critical for valuation, leasing, and risk management in aviation. Traditional appraisal and cost-based approaches often fail to capture the nonlinear effects of market cycles and macroeconomic conditions. This study applies machine learning to predict the current fair market value (CFMV) of Airbus and Boeing narrow-body air- craft using a rolling-origin evaluation framework. The feature set integrates appraisal-standard variables (age, delivery year, subtype) with macroeco- nomic indicators such as the consumer price index, jet fuel price, interest rates, and air traffic indices. We benchmark regularized linear models against ensemble methods, finding that gradient boosting (XGBoost) consistently de- livers the strongest performance, achieving mean absolute percentage error (MAPE) below 5% and R^2 near 0.90. Residual analysis confirms stable accu- racy across aircraft types, while depreciation surface visualizations illustrate how lifecycle aging and market shifts interact to shape values. Results in- dicate that lifecycle and technical characteristics dominate predictive power. These findings demonstrate the potential of machine learning to enhance traditional appraisal practices.
Keywords. Aircraft valuation; Depreciation modeling; Rolling-origin forecasting; Gradient boosting; Aviation finance.
JEL. C23; D24; O14; O31; O33.

1. Introduction

Accurate modeling of aircraft depreciation is essential for understanding asset values and structuring financing arrangements in the aviation industry. Aircraft depreciation is ultimately linked to customer demand, since willingness to pay for air travel shapes airline revenues, which in turn determines fleet utilization, residual values, and long-run depreciation patterns Buchmann (2025). Since more than half of the global commercial fleet is leased rather than owned outright, residual value risk has become a defining factor in both operating and financial lease contracts. Recent reviews emphasize that depreciation is not only a technical consideration but also a strategic financial variable that shapes industry dynamics and contract negotiations Wandelt et al. (2023). Rode et al. (2002)

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show that uncertainty in residual values is the greatest risk to lessors in lease financing, and that even small misestimations of depreciation curves can lead to large financial losses. Cost estimation and valuation models for aircraft are often decades old and require reevaluation for modern conditions Shahriar et al. (2022).

Aircraft represent one of the largest categories of transport infrastructure assets and have increasingly been treated as a distinct investment class over the past decades Yu (2020). The global aviation sector supports roughly US$4.1 trillion in economic activity at about 3.9% of world GDP and involves 86.5 million jobs worldwide Economics and Group (2024). Their values are shaped not only by technical aging and maintenance cycles, but also by macroeconomic forces, regulatory environments, and shifts in airline business models. With more than half of the global fleet leased rather than owned, accurate valuation has become central to managing residual value risk, structuring financing arrangements, and pricing leases. Yu (2020) emphasizes that appraisal values are provided by independent third parties under standardized definitions, but they remain sensitive to prevailing mar- ket conditions and assumptions about future use. This dual role of aircraft as both physical operating assets and financial instruments underscores the importance of robust, data-driven approaches to analyzing depreciation and value dynamics.

Machine learning offers powerful tools for modeling depreciation because it can capture non-linear patterns, incorporate heterogeneous data sources, and adapt to structural changes over time. Ye et al. (2024) highlight how ML methods ranging from supervised learning and ensemble approaches to deep neural networks, graph-based models, and reinforcement learning have transformed asset pricing by improving prediction accuracy and enabling dynamic adaptation to changing market conditions. These same advantages are relevant for aircraft depreciation modeling, where asset values depend on complex interactions among technical, operational, and macroeconomic variables.

In this paper, we apply these capabilities by building Rolling origin forecasting models of narrow-body aircraft current market value. We evaluate both regularized linear models and ensemble learning methods, finding that gradient boosting delivers the most stable out-of-sample accuracy across Boeing and Airbus variants. By incorporating appraisal-standard features such as age, delivery year, and variant identifiers alongside macroeconomic drivers including CPI, jet fuel price, interest rates, and traffic indices, our framework produces depreciation surfaces that capture price changes across varying market conditions and different points in time.

We use a feature set that combines both lifecycle and macroeconomic drivers of aircraft value. Appraisal-standard characteristics such as age, delivery year, and variant identifiers are included to capture the orderly progression of depreciation across vintages, as emphasized by industry analyses of market value determinants (Ackert, 2012). To account for external influences, we incorporate macroeconomic variables such as consumer price index (CPI), jet fuel price, interest rates, and traffic indices, which have been shown to fundamentally shape operating costs and residual values (Gordon, 1990). By integrating these intrinsic and extrinsic factors, our framework provides a comprehensive basis for modeling aircraft depreciation dynamics.

2. Literature review

Nelson & Caputo (1997) examined depreciation dynamics in single -and twin-engine aircraft, showing that both deterioration and depreciation rates respond systematically to economic factors such as liability costs and maintenance expenses, rather than being constant exogenous parameters. Their findings highlight the importance of treating depreciation as an endogenous process, aligning with our manuscript's focus on modeling aircraft value tra- jectories using data-driven approaches that incorporate market and macroe- conomic influences. Geursen et al. (2023) applied an Advantage Actor–Critic (A2C) reinforcement learning algorithm to airline fleet planning, explicitly modeling demand and fuel price uncertainty.

Vasigh et al. (2020) proposed a modified discounted cash flow (DCF) framework to capture both revenue and cost dynamics in aircraft valuation, demonstrating that passenger yield, maintenance, and fuel costs exert the greatest influence on asset values. Their sensitivity analysis using Monte Carlo simulations underscores how valuation outcomes vary with economic fluctuations, which complements our focus on data-driven forecasting approaches that integrate lifecycle depreciation patterns and macroeconomic factors. Earlier perspectives on financial evaluation emphasized direct operating cost comparisons and net present value analysis, but also highlighted the limitations of these methods in capturing residual value risk and flexibility Gibson & Morrell (2004). More recent modeling has explicitly incorpo- rated depreciation costs in optimization frameworks for fleet planning. For instance, Chen et al. (2018) propose a mathematical programming model for airlines that evaluates operating leases, capital leases, and purchases under budget and debt constraints, showing how depreciation affects acquisition strategies.

Gilligan (2004) investigated adverse selection in the used business aircraft market, showing that depreciation rates are proportional to trading volumes for less reliable brands, consistent with the classic "lemons" problem. Importantly, the study highlights how leasing arrangements mitigate asymmetric information by increasing the average quality of aircraft entering the resale market. These findings complement our manuscript's emphasis on modeling aircraft values under heterogeneous market conditions, where both information frictions and institutional mechanisms influence observed depreciation trajectories. Recent studies have also examined how regulatory changes (e.g., IFRS 16) and fluctuations in demand, interest rates, and exchange rates af- fect aircraft acquisition strategies Chen & Wu (2023).

Bergmann & Feuerriegel (2025) advanced resale value prediction by incorporating highly granular vehicle equipment information into machine learning models, demonstrating a statistically significant improvement in accuracy. Their use of automated feature engineering and explainability techniques (e.g., SHAP values) highlights how nuanced asset characteristics can enhance model interpretability and business decision-making. These insights are directly relevant to our aircraft valuation study, where incorporating detailed technical and usage attributes may likewise improve predictive per- formance beyond standard depreciation models.

3. Methodology

3.1. Current fair market value (CFMV)

A clear definition of CFMV is essential to ensure consistency and comparability across aircraft appraisals, financial modeling, and regulatory reporting. Establishing this definition provides the foundation for our analysis and allows us to align predictive modeling with industry-standard appraisal practices. We follow the ISTAT standard.

Definition 3.1 (Current Fair Market Value). Current Fair Market Value is the appraiser's opinion of the most likely trading price that may be generated for an aircraft under the market circumstances that are perceived to exist at the time in question. Market Value assumes that the aircraft is valued for its highest, best use, that the parties to the hypothetical sale transaction are willing, able, prudent and knowledgeable and under no unusual pressure for a prompt sale and that the transaction would be negotiated in an open and unrestricted market on an arm's length basis, for cash or equivalent consideration and given an adequate amount of time for effective exposure to prospective buyers Yu (2020).

A formal appraisal seeks to provide a CFMV. Appraising an aircraft is essential to establish its value for transactions such as sales, leases, and loan collateral, as well as for determining residual insurance required and lease rates. It also provides a reliable basis for fleet valuation in mergers or bankruptcies, property tax assessments, and values acceptable to tax authorities for contributions to entities such as aviation schools and museums.

Market value is typically determined through appraisal-based methods that consider recent comparable transactions, adjustments for aircraft age, maintenance condition, and economic environment. Appraisers rely on stan- dardized definitions and valuation approaches, including cost, income, and market comparison methods, to provide consistent benchmarks across aircraft types. These approaches ensure that market value reflects both technical asset characteristics and prevailing macroeconomic conditions, as em- phasized in Section 5.2.2 of Yu (2020).

3.2. Data and features

We use year-frequency observations aligned by delivery year and target year for multiple narrow-body variants. Table 1 summarizes the features used in our models, grouped by category. Prior research confirms that technical aircraft characteristics such as seating capacity, range, and performance measures are strong determinants of market value Plötner et al. (2012). Similarly, hedonic analyses of aviation externalities show that estimated values can vary significantly depending on methodology, as highlighted in a meta- analysis of aircraft valuation noise Schipper et al. (1998). Feature importance scores were extracted from XGBoost gain metrics. To ensure transparency in our machine learning models, we apply SHAP analysis to interpret feature contributions. This aligns with best practices outlined by Ponce-Bobadilla et al. (2024).

The dataset contains nearly 200,000 observations. Key attributes include aircraft descriptors such as Body Type, Manufacturer, Plane Type, Sub-Type, and Year of Delivery. For example, a narrow-body airplane refers to a single aisle aircraft, typically seating between 100 and 240 passengers and designed for short to medium-haul flights. The dataset spans a broad historical window, covering aircraft values from 1995 through 2020. Within this period, it captures market information for a wide range of aircraft, totaling 171 unique narrow-body plane types. Types chosen for analysis, Airbus A321-200, Boeing 737-700, and Boeing 737-800 are particularly well represented. Each of these types contributes on the order of 10 000 data points, providing robust samples for analysis.

Macro indicators are sourced from public series: CPI, jet fuel/crude, and the 10-year rate from FRED, and air-traffic indices from ICAO (Federal Reserve Bank of St. Louis, 2025a, b, c; International Civil Aviation Organization, 2025). CFMV values are reported in millions (USD).

We aggregated aircraft valuation panels from IBA Group, Collateral Ver- ifications LLC and BK Associates, and standardized them to a common schema (types, units, and time alignment). We then applied cleaning and data-quality checks for completeness, validity, range/consistency rules, and referential integrity; missing or inconsistent fields were corrected where possible using crosssource reconciliation. Outliers were identified via interquartile range (IQR) and removed from the aircraft price data to mitigate the influence of transactions driven by extraordinary circumstances (e.g., distressed sales, lease restructurings, or atypical market shocks) that do not reflect underlying market value dynamics. Finally, the sources were time-aligned and joined on canonical identifiers, and duplicate records were resolved using joins.

Table 1. *Feature set used for rolling-origin evaluation, after feature engineering. XGBoost column reports grouped total-gain share %. SHAP column shows grouped mean |SHAP|.*

Feature	Description	XGBoost Importance	SHAP
Categorical (encoded)			
Manufacturer	Aircraft manufacturer (e.g., Boeing, Airbus)	0.330	1.003
Family	Aircraft family (e.g., 737, A320)	5.175	0.602
Plane type	Official type category (e.g., narrow-body)	1.899	2.776
Subtype	Subclassification of type	22.297	0.593
Age / Cohort			
Age (years)	Effective age in years	1.050	2.443
Age^2	Curvature term for depreciation	2.312	1.463
Age bucket	Coarse age grouping (e.g., 0–5, 6–10)	1.132	0.761
Delivery year	Year the aircraft was delivered	< 0.05	0.571
Temporal / PIT alignment			
Calendar year	Year of observation	3.621	0.330
Month/Year source	Month/Year of the data source	7.446	1.982
Target			
CFMV	Current Market Value		
External Macros (yearly)			
CPI	Consumer Price Index	1.527	0.091
Jet fuel price	Energy / crude proxy	< 0.05	< 0.05
10-year rate	U.S. 10-year Treasury yield	< 0.05	< 0.05
Air traffic index	ICAO air transport traffic index	< 0.05	< 0.05

Table 1 shows that subtype identifiers and age contribute the largest predictive power, while cohort features capture the non-linear progression of depreciation. XGBoost importance reflects the relative contribution of each feature to model gain, while SHAP values quantify the average marginal impact of each feature on individual predictions. Overall, technical aircraft characteristics dominate the prediction of market values, with macro variables having relatively low predictive power.

3.3. Performance evaluation

To assess the predictive accuracy of the proposed models, we employ two primary performance metrics: the coefficient of determination (R^2) and the Mean Absolute Percentage Error (MAPE), as they are widely applied in recent aviation machine learning studies to jointly capture explanatory power and relative forecast accuracy Szrama & Lodygowski (2024). These metrics capture complementary aspects of model performance. R^2 measures the proportion of variance in the target variable explained by the model, thereby indicating goodness-of-fit, while MAPE quantifies the relative size of prediction errors, offering an intuitive percentage-based interpretation of accuracy.

The R^2 statistic is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{N}\left(y_i - \bar{y}\right)^2}$$

where y_i denotes the observed value, $\hat{y}_i$ the predicted value, $\bar{y}$ the mean of observed values, and N the number of samples. An R^2 close to 1 indicates that the model explains most of the variation in the data, while lower or negative values reflect poor explanatory power.

$$MAPE = \frac{100}{\mathrm{N}} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

This metric is scale-independent and particularly useful for expressing forecasting accuracy in financial and asset valuation contexts.

3.4. Models

We evaluate regularized linear baselines (ridge, elastic net) and ensemble trees (random forest, gradient boosting, XGBoost, LightGBM) with version-safe early stopping for boosters. XGBoost consistently delivered the strongest predictive performance, with lower mean errors and greater stability across aircraft variants compared to all other models. In the remainder of this paper, we focus on reporting the XGBoost results, including its forecasting accuracy and interpretability analysis.

3.5. Rolling-origin evaluation

While our study applies rolling-origin forecasting with ensemble learning, prior work on loan and lease modeling emphasizes Monte Carlo simulation of defaults, value shocks, and interest rate fluctuations Hallerstrom (2020).

Model performance was assessed using a rolling origin evaluation framework, which mirrors real-world forecasting conditions by progressively updating the training window over time. Under this design, the model is initially trained on all observations available up to a chosen cutoff year and subsequently evaluated on the immediately following period. The cutoff is then advanced sequentially, with the model retrained and retested at each step. A minimum of 5 years of historical data was required for each evaluation. The training window was advanced in increments of 1 year and forecasts were 3 years ahead.

To ensure the validity of our predictive modeling framework, we applied the Cramé–von Mises two-sample test as described in Erlemann (2021) to compare the training and test datasets. This nonparametric goodness-of-fit procedure evaluates whether two samples are drawn from the same under- lying distribution. By confirming distributional similarity between training and test subsets, we mitigate the risk of model bias due to covariate shift and ensure that performance metrics reflect genuine generalization rather than artifacts of sampling imbalance.

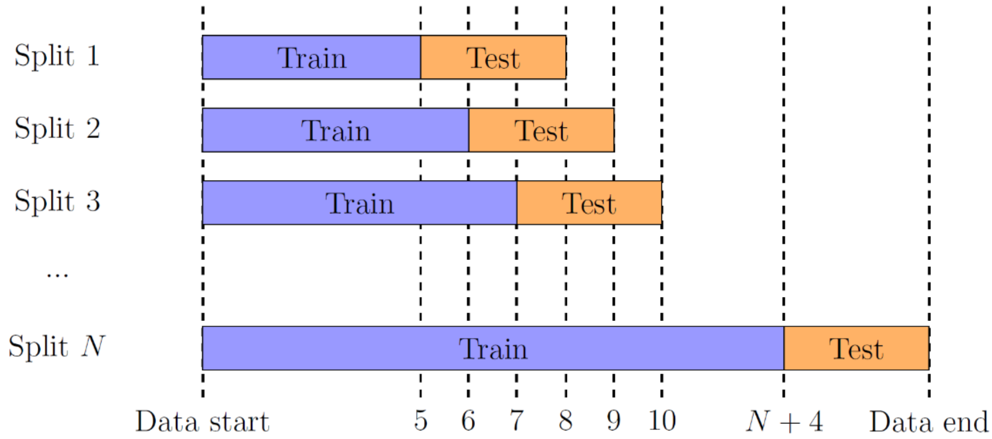

Figure 1. *Rolling origin evaluation: the training window expands forward in time, and the fixed size test set is rolled forward by 1 year.*

4. Results

4.1. Model accuracy

Figure 2 presents rolling-origin forecasting results for CFMV at a prediction horizon of $H = 3$ across the Airbus A321-200, Boeing 737-700, and Boeing 737-800. For the A321-200, the mean absolute percentage error (MAPE) rises from approximately 3% in 2005 to above 5% in 2007, before stabilizing around 4–4.5%. The 737-700 achieves the lowest initial error (just over 2%), peaks at roughly 4.8% in 2007–2008, and then remains in the 4–4.6% range. The 737-800 shows an increase from 2.2% in 2005 to nearly 5% in 2009, followed by a decline to about 3.5% by 2012.

Turning to R^2, the A321-200 improves steadily from 82% in 2005 to more than 94% by 2012. The 737-700 starts near 93%, declines to below 82% in 2007, but subsequently recovers to 93% by 2012. The 737-800 demonstrates consistent gains, moving from 91% in 2005 to over 95% by 2012. Overall, performance improves with the length of the training window, with all three variants ultimately achieving $R^2 > 93\%$ and MAPE below 5%.

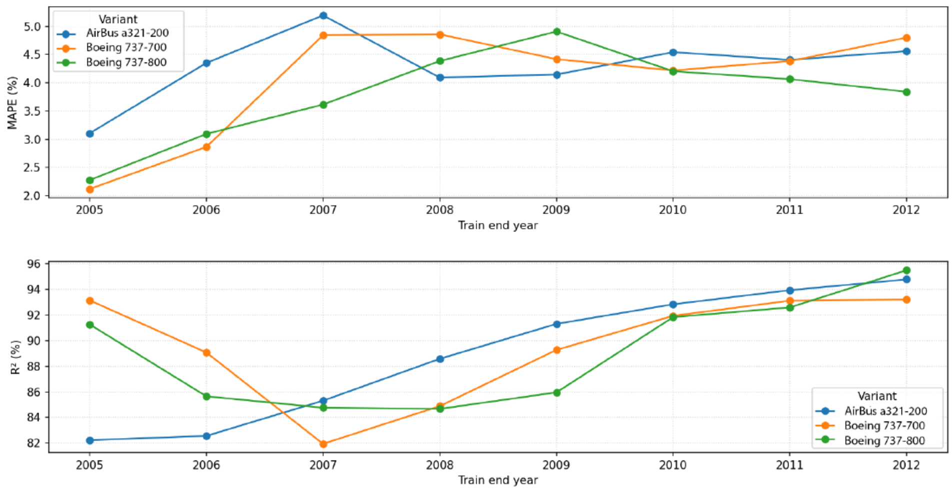

Figure 2. *CFMV rolling-origin evaluation. Top graph shows MAPE (%) vs. train-end year and bottom graph shows R^2 (%). Legend uses official plane type and variant.*

4.2. Example

Figure 3 indicates that prediction errors are small across all three variants, generally within 1 unit of CFMV. The Airbus A321-200 shows consistent overpredictions, with errors increasing toward 2015. The Boeing 737-700 alternates between minor over- and underpredictions, reflecting balanced accuracy overall. In contrast, the Boeing 737-800 tends to be modestly underpredicted in the later years, though errors remain stable and limited. Since the models were trained on data from 2005–2012 and evaluated on the 2013–2015 horizon, these results demonstrate that the framework captures depreciation dynamics consistently while maintaining only minor variant-specific biases in the out-of-sample period.

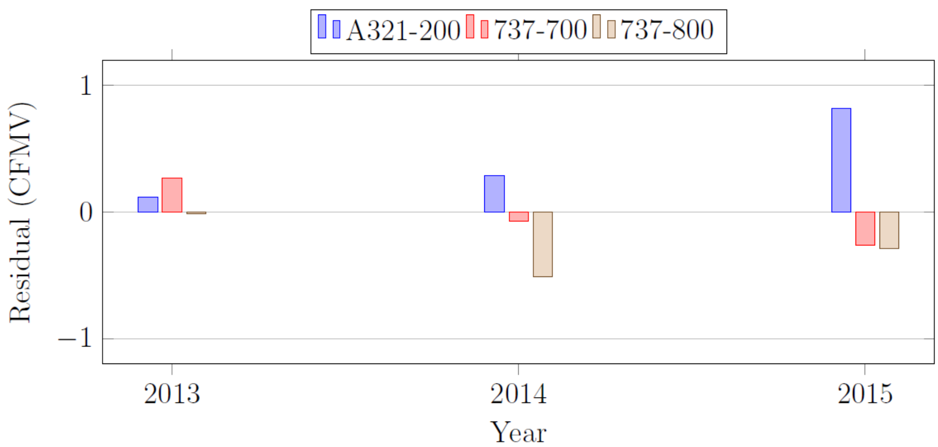

Figure 3. *Residuals for 2013–2015 by variant. Positive bars indicate overprediction; negative bars indicate underprediction.*

4.3. Depreciation Surface

A depreciation surface is a two-dimensional representation of how asset values decline jointly with age and calendar time. It visualizes annual depreciation rates across both lifecycle effects and market effects, as economic or industry conditions change over years. By combining these dimensions, the surface highlights how technical aging and external shocks together shape the trajectory of fair market values.

Figure 4 presents the depreciation surface for Boeing 737-700 aircraft, showing the evolution of annual depreciation rates as a function of both aircraft age and observation year. The color gradient highlights lifecycle and market dynamics: younger aircraft (0–5 years) experience relatively modest depreciation in the 4–6% range, while mid-life aircraft (6–15 years) depreciate more steeply, often between 6–8%. Older aircraft exhibit the highest rates, exceeding 8% annually, reflecting diminished market demand and increasing maintenance costs. Time-dependent variation is also evident, with lower depreciation observed during market downturns (e.g., 2008–2009) and sharper declines during periods of oversupply, notably post-2020. The dashed line marks the start of the forecasting horizon, where projected depreciation rates remain elevated due to continued fleet replacement pressures and limited secondary market resilience.

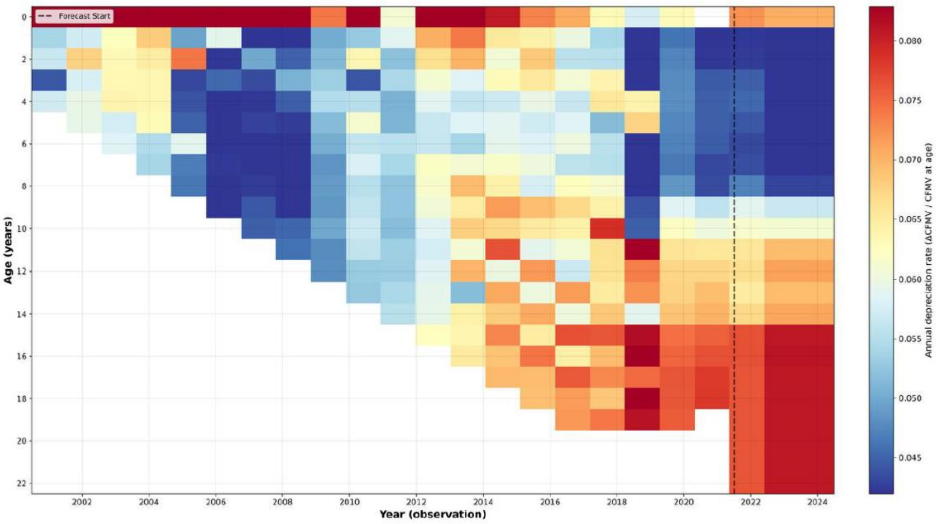

Figure 4. *Annual Depreciation Rates of Boeing 737-700 Aircraft Across Age and Observation Years.*

Figure 5 shows the depreciation surface for Boeing 737-800 aircraft, illustrating annual depreciation rates across aircraft age and observation year. Similar to the 737-700, younger aircraft (0–5 years) depreciate more gradually, while mid-life and older aircraft experience steeper declines. Timedependent patterns highlight periods of accelerated depreciation, particularly after 2010, followed by stabilization in later years. The dashed line again denotes the start of the forecasting horizon, with depreciation remaining elevated due to sustained replacement pressures from next-generation aircraft. Compared to the 737-700 (Figure 4), the 737-800 exhibits less extreme volatility across market cycles and maintains lower depreciation rates at mid-life ages. This reflects the stronger and more enduring market demand for the 737-800, which benefited from larger operator bases and greater alignment with fleet replacement strategies.

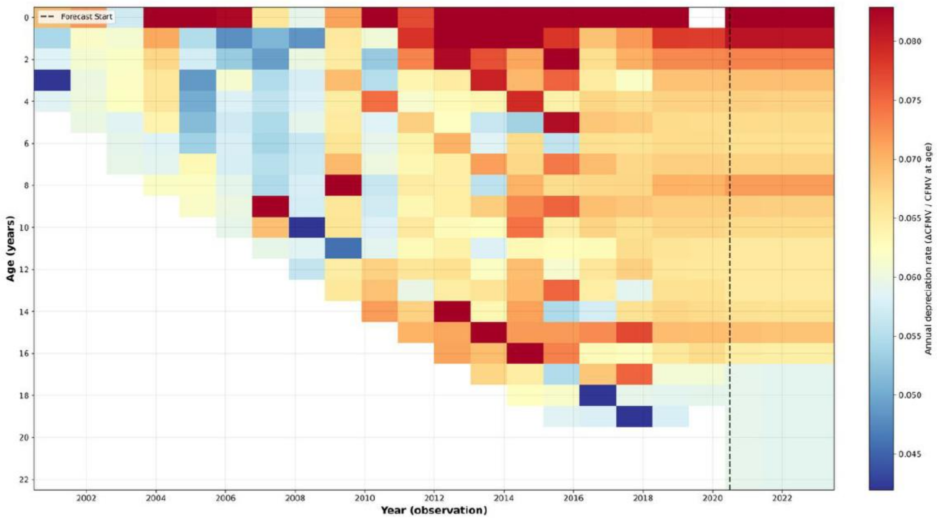

Figure 5. *Annual Depreciation Rates of Boeing 737-800 Aircraft Across Age and Observation Years.*

5. Conclusion

This study demonstrates the effectiveness of machine learning, and gradient boosting in particular, for forecasting aircraft current market values. Using a rolling-origin evaluation framework, the models achieved stable accuracy across Airbus and Boeing narrow-body variants, with mean MAPE below 5% and R^2 values near 0.90. While technical features such as age, subtype, and cohort were the dominant drivers of predictive power, incorporating macroeconomic indicators provided little predictive power. The results confirm that aircraft depreciation is shaped mostly by lifecycle dynamics, and that modern ensemble methods can capture these interactions with high reliability. These insights support the use of machine learning for valuation, lease structuring, and risk management, and the findings are consistent with prior aviation valuation and fleet economics literature that emphasizes lifecycle effects and replacement dynamics (Yu, 2020; Bazargan & Hartman, 2012).

Depreciation modeling has important implications for lessors, investors, and airlines, as more accurate forecasts of aircraft values can improve lease structuring, risk management, and capital planning. By quantifying depreciation trajectories with high out-of-sample accuracy, our framework provides a data-driven complement to traditional appraisal practices, enhancing transparency and decision-making in aircraft finance. Future work could extend this approach by incorporating higher-frequency transaction data, exploring the role of maintenance and utilization patterns in greater detail. Also, future research could expand depreciation modeling to fully integrate aircraft financing frameworks, linking asset value forecasts with lease structures, debt service, and equity returns. Such an approach would connect depreciation dynamics with airline revenue generation and cash flow capacity, offering a holistic view of how asset values interact with financing decisions and profitability.

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CRediT Author(s) Statements:

Contribution	D Yu	R Erlemann	CC Morris	
Conceptualization				
Methodology				
Software				
Validation				
Formal analysis				
Investigation				
Resources				
Data curation				
Writing –original draft				
Writing –review & editing				
Visualization				
Supervision				
Project administration				
Funding acquisition				

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