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Research on Identification of Cost Drivers and Profitability Analysis from the Perspective of Large Enterprise P&L Management

Siyao Li

Finance Department, OMD USA, New York, 10001, United States

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Abstract: This study constructs an analytical framework of "operating activities—categorized costs—unit costs—operating profit margin" to assess the verifiability of categorized cost budgeting and profit analysis for large enterprises. Using publicly available official data from the United States, this study generates quarterly observations for 702 enterprises from 14 large scheduled passenger transport companies from 2012 to 2025. Two-way fixed effects, multi-driver models, a complete hierarchical asymmetric model, and fixed-time out-of-sample tests are employed to identify cost drivers. The results show that fuel consumption and actual fuel prices are the most stable project drivers. Compared to the ASM model, the multi-driver model reduces the RMSE of operating costs and fuel costs by 10.0% and 18.8% respectively during the test period, but personnel, maintenance, and depreciation costs do not show stable predictive gains. The complete hierarchical model does not support the notion that fixed asset density generally enhances cost stickiness. The contemporaneous coefficients for categorized unit costs and operating profit margin are both negative, but the joint test is insignificant, and the lag relationship is weaker. These results indicate that profit and loss management for large enterprises should configure categorized drivers according to resource consumption mechanisms and distinguish between contemporaneous accounting correlations, conditional forecasts, and long-term causal effects.

1 Introduction

In large enterprises, profit and loss management connects business planning, resource allocation, budget control, and performance evaluation. The focus of profit and loss management is not on repeatedly explaining the difference between revenue and expenditure at the end of the period, but on identifying which operating activities and resource constraints contribute to various costs. The group headquarters typically organizes budgets based on revenue, expense ratios, and profit margins, while business units allocate resources based on output, working hours, equipment, orders, and contracts. If these two sets of metrics cannot be consistently converted, a uniform revenue and expense ratio will mask the different roles of quantity, efficiency, price, and asset structure, making it difficult to trace budget deviations down to specific stages.

Data analytics tools are driving management accounting from experience-based allocation to verifiable cost estimation[1]. Existing research has found that cost adjustment characteristics are related to the accuracy of profit forecasting[2]. Debt covenants can influence a company's decision to retain committed resources[3], and personnel efficiency and external oversight can also change the rate of adjustment of labor costs[4]. These studies suggest that costs are not a fixed proportion of revenue, and business expansion and contraction are not necessarily symmetrical. However, existing research often uses operating revenue to explain aggregate costs, and the correspondence between categorical costs and activity drivers still lacks testing. Existing model evaluations are mostly limited to within the sample, and whether adding new drivers can improve the estimation of samples outside the fixed time period still needs to be answered separately.

Profit and loss management also requires that cost driver identification be linked to profitability analysis. The significance coefficients in the cost equation only reflect contemporaneous responses and do not equate to improved budget accuracy. Categorized costs are directly entered into the income statement, and the contemporaneous negative correlation between unit cost and profit margin may partly stem from accounting composition. Researchers who fail to distinguish between mechanism identification, conditional prediction, and profitability associations are prone to confusing statistical significance, predictive gain, and causal effects. Based on this consideration, this study does not presuppose that multi-driver models are necessarily superior to simple models, nor does it use expected signs to replace robust inferences.

Large airlines simultaneously disclose profit and loss statements, categorized costs, assets, and quarterly operating volumes. This data provides a verifiable research scenario for observing the "activity-cost-profit" chain. This study does not rank the profitability of airlines, nor does it generalize industry parameters to all large companies. This study focuses on answering three interrelated questions: Are there differences in the cost estimation capabilities of revenue, core business volume, and mechanism-based multi-driver models? Do fuel, personnel, maintenance, and depreciation have their own cost drivers and asymmetric adjustments? Is there a stable contemporaneous and lagged relationship between categorized unit costs and operating profit margin?

This study places cost formation mechanisms, robust inference based on few clusters, and out-of-sample evaluation at fixed time within the same framework. The study design allocates drivers according to resource consumption relationships, compares the model's predictive performance during stress and normal testing periods, and distinguishes between contemporaneous and lagged information in unit costs across categories. This design avoids directly interpreting in-sample significance as budget effectiveness and provides a verifiable methodological reference for other large enterprises to conduct category-based profit and loss analysis.

2 Research Methods

2.1 Research Design and Data Sources

This study employs a retrospective quarterly panel design. Financial, asset, and operational data are from the U.S. Bureau of Transportation Statistics, fuel prices are from the U.S. Energy Information Administration, and the GDP deflator is from FRED. The study sample covers large Group III domestic scheduled passenger transport companies in the United States from the first quarter of 2012 to the fourth quarter of 2025.

This study uses Airline ID and quarterly data, and removes records with non-positive operating revenue, operating costs, or ASM. The sample retains loss quarters and requires each company to have at least 24 valid quarters. The filtered sample includes 14 companies and 702 company-quarter observations. This study does not interpolate panel gaps and only uses records with consecutive adjacent quarters and complete variables. There was an abnormal contraction in aviation activity in 2020-2021 [5], and this period is listed as a stress period in this study . Data verification was performed by checking the accounting equation and the workload relationship; the core fuel results remained stable when the minimum historical period was changed to 16 or 32 quarters.

2.2 Variable Construction

C_{kit}This represents $i$the total cost of category I incurred by the firm $k$in a quarter, expressed in thousands of US dollars. The dependent variables in $t$this study include total operating costs, and four categories of costs: fuel, personnel, direct maintenance, and depreciation of flight equipment. Direct operating costs, which are cross-summed with category items, are no longer used in this study. The amounts are first converted to constant prices using the GDP deflator, and then the logarithmic differences between adjacent quarters within the firm are calculated. Since this is not the CASM (Conditional Cost of Operations), the model C_{kit}retains ASM as an explanatory variable for activity levels.

This study categorizes candidate drivers into six types: size, time, frequency, resource commitment, external price, and structure. ASM represents total capacity, while flight hours and takeoffs reflect duration and cycle frequency, respectively. Days in service represent the asset commitment undertaken by the company to maintain aircraft operations, and fleet complexity equals one minus the sum of squares of the ASM share of each aircraft type. Existing research shows that fuel type and energy prices can change the cost structure of airlines [6], while fleet composition is related to asset allocation and maintenance efficiency [7]. To unify the monetary caliber, this study converts EIA nominal fuel prices to real prices using the GDP deflator. Fuel price exposure equals the product of the logarithmic change in real prices and the proportion of fuel costs to operating costs in the previous period.

Table 1. Descriptive statistics of key variables

Variable	Definition	Mean	Standard deviation
OperatingMargin	Operating profit / Operating revenue	-0.0235	0.4025
RASM	Unit ASM Revenue	0.1438	0.0475
CASM	Unit ASM operating cost	0.1430	0.0595
LoadFactor	Revenue per kilometer/ASM	0.8088	0.0968
RealFuelPrice	Actual quarterly average price of aviation fuel	2.0188	0.6818
Utilization	Total aircraft hours / number of days in use	7.4877	2.3410
FleetComplexity	1 - Sum of Squared ASM Shares for Each Model	0.6114	0.1725
FixedAssetDensity	Net property and equipment / Revenue for the past four quarters	0.9142	0.6136

This study calculates fixed asset density by dividing net property and equipment by operating revenue over the past four quarters, with M3 using a lagged and centralized value. Robustness checks use the ratio of net property and equipment to total assets as an alternative. This study uses operating profit margin to measure profitability and calculates unit costs by dividing fuel, crew, maintenance, and depreciation costs by ASM, respectively. The contemporaneous model uses adjacent quarterly changes in unit costs, while the lagged model uses previous period changes. These two settings help distinguish between in-report composition and inter-period information. Descriptive statistics for key variables are shown in Table 1.

2.3 Model Specification and Statistical Analysis

This study uses the income-only driver model M0 and the capacity-only driver model M1 as simple benchmarks. The two models can be uniformly expressed as follows:

$$\Delta \ln C_{kit} = \alpha_k + \beta_k \Delta \ln Z_{it} + \mu_i + \lambda_t + \varepsilon_{kit}, Z \in \{\text{Revenue}, \text{ASM}\}$$

The multi-factor model M2 uses M1 as a nested restricted model. The operating cost equation incorporates flight hours, number of takeoffs, fuel price exposure, utilization rate, and fleet complexity. The fuel cost equation incorporates fuel consumption, actual fuel price, and flight hours; the personnel cost equation incorporates flight hours and number of takeoffs. The maintenance cost equation incorporates flight hours, days in service, and fleet complexity; the depreciation cost equation incorporates days in service and fleet complexity. The general form of M2 is:

$$\Delta \ln C_{kit} = \alpha_k + \beta_k \Delta \ln \text{ASM}_{it} + \sum_j \eta_{kj} D_{jit} + \mu_i + \lambda_t + \varepsilon_{kit}$$

The asymmetric model M3 refers to Anderson et al. [8]'s setting of business descent interaction terms. M3 follows the hierarchical principle of interaction models and fully incorporates the main effects and all low-order interaction terms:

$$\Delta \ln C_{kit} = \alpha_k + \sum_j \beta_{kj} D_{jit} + \phi_{1k} \text{Down}_{it} + \phi_{2k} \widetilde{\text{AID}}_{i,t-1} + \gamma_k Q_{it} + \phi_{3k} R_{it} + \phi_{4k} S_{it} + \delta_k T_{it}$$
$$+ \mu_i + \lambda_t + \varepsilon_{kit}$$

DownThe value is 1 when ASM decreases. The variables $Q$are equal to Down $\times$ $\Delta\ln$ASM, the variables $R$are equal to $\widetilde{\text{AID}}$ $\times$ Down, the variables $S$are equal to $\widetilde{\text{AID}}$ $\times$ $\Delta\ln$ASM, and the variables $T$are equal to $\widetilde{\text{AID}}$ $\times$ Down $\times$ $\Delta\ln$ASM. The coefficient $\gamma_k < 0$represents the weaker cost response during the contraction period compared to the expansion period under the average asset structure. The coefficient $\delta_k$represents the conditional marginal difference in the asymmetric response as the initial asset structure changes. Fixed asset density is a relatively slow-changing structural variable and $\delta_k$should therefore be considered as a structural conditional marginal effect, rather than the short-term dynamic elasticity of fixed asset density itself. This study defines the coefficient of logarithmic change between adjacent quarters as the short-term arc elasticity and does not directly extrapolate this coefficient to an annual or long-term parameter.

Profitability analysis does not estimate identity-based regressions between total RASM, total CASM, and profit margin. This study examines the contemporaneous and lagged correlations between categorical unit costs and operating profit margin:

$$\Delta \text{Margin}_{it} = a + \sum_{m \in \mathcal{K}} \theta_m \, \Delta \text{CASM}_{mit} + \mu_i + \lambda_t + u_{it}$$

$$\Delta \text{Margin}_{it} = b + \sum_{m \in \mathcal{K}} \rho_m \, \Delta \text{CASM}_{m,i,t-1} + \mu_i + \lambda_t + v_{it}$$

Except for the fuel cost equation, each structural model controls for firm and calendar quarter fixed effects. The actual fuel price is the same for all firms in the same quarter, and this variable is completely collinear with the calendar quarter fixed effects. Therefore, the fuel equation controls for firm and seasonal fixed effects and adds a firm-quarter bidirectional clustering test. The sample has only 14 firm clusters, and the ordinary CR1 standard error is only used for description. The main inference of this study adopts the null hypothesis-restricted Wild Cluster Bootstrap-t and enumerates 2^{14}Rademacher weights with firms as the resampling level. This method is suitable for robust inference under the condition of few clusters [9].

The WCB test first applies a zero constraint to the coefficient to be tested, then generates a bootstrap sample using the constrained model residuals, and re-estimates the studentized statistic. The two-tailed p-value is equal to the proportion of weighted combinations whose absolute value of the simulated statistic is not less than the absolute value of the original statistic. The weighted combinations corresponding to the 14 companies can be completely enumerated; therefore, the results in Table 2 are not affected by the number of random repetitions.

The structural coefficients were estimated using the full sample from 2012 to 2025, while the conditional forecasts were divided into samples according to time. 2012–2019 constituted the training period, 2020–2021 constituted the stress period, and 2022–2025 constituted the fixed-time test period. The test period model used the operational drivers that had been achieved or were given in the budget during the same period, so the test evaluation corresponds to the conditional cost estimate, rather than the ex-ante forecast under unknown operational conditions. In this study, M0, M1, and M2 were compared on the common effective sample of each cost item, and the actual cost during the test period was not included in the estimation of the forecast parameters. Evaluation indicators included MAE, RMSE, and out-of-sample relative to the “zero cost change” benchmark R^2. The nested model used the Clark-West adjusted loss test [10]. The test summarizes the error over 16 test quarters, uses the 3-lagged HAC variance, and reports both $t_{15}$the one-sided p-value and the bootstrap p-value of the cyclic block of length 4.

In this study, negative values indicate that the multi-factor model is inferior to the benchmark, calculated out of the sample . The Clark-West test sets the smaller M2 prediction error R^2as the alternative hypothesis, and cyclic block resampling preserves the correlation between errors in adjacent quarters. The stress period is only used for independent error assessment. $1 - \mathrm{MSE}_{M2}/\mathrm{MSE}_{Benchmark}$This study does not use stress period results to select the test period model, nor does it adjust the training window based on stress period results.

Robustness tests in this study included 1% two-tailed reduction for continuous variables, exclusion of the pandemic period, 499 firm-group bootstraps, stress period assessment, the lowest historical period count for 16/32 quarters, and a substitute caliber for the proportion of fixed assets to total assets. Firm-group bootstraps were sampled from the firm as a whole to preserve time correlations within firms. This study used Python 3.12, pandas 2.3, and statsmodels 0.14 for analysis, and the original file hashes, filtered audits, analysis panels, and results tables were saved separately.

3. Research Results

3.1 Classification Cost Drivers

The sample's operating profit margin has a mean of -2.35%, a median of 6.36%, and a standard deviation of 40.25%. The distribution characteristic of a mean lower than the median indicates that a few severely loss-making quarters during the pandemic significantly lowered the overall mean. The sample's load factor is 80.88%, and the fleet complexity is 0.611. The operating cost, fuel, personnel, and maintenance models contain 684, 633, 687, and 684 valid observations, respectively, while the depreciation model contains 679 valid observations.

Table 2 shows that the short-run arc elasticity of fuel cost consumption is 0.770, and the short-run arc elasticity of actual fuel price is 0.746, with corresponding WCB p-values of 0.006 and less than 0.001, respectively. The p-values for both firm-quarter bidirectional clustering are less than 0.001, indicating that the correlation treatment for common price shocks did not change the judgment. The ASM coefficient for operating costs is 0.141, with a p-value of 0.093; the fuel price exposure coefficient is 0.841, with a p-value less than 0.001. The ASM coefficient for maintenance costs is 0.367, with a p-value of 0.033, but after 1% tailing, the coefficient decreases to 0.241, and the p-value increases to 0.063. The fleet complexity coefficient for depreciation costs is 0.772, with a p-value of 0.058, and after tailing, the p-value is 0.112. The various tests show clear differences in evidence: fuel quantity and actual price are the most stable classification drivers, while the evidence for maintenance capacity and fleet complexity is weaker.

Table 2. Main Estimation Results of Category Cost Drivers

Cost items	Motivation	Coefficient	WCBp value	Enterprise Bootstrap 95% range
Operating costs	ASM changes	0.141	0.093	[-0.019, 0.351]
Operating costs	Fuel price exposure	0.841	<0.001	[0.584, 1.133]
fuel costs	Fuel consumption	0.770	0.006	[0.413, 1.366]
fuel costs	Actual fuel price	0.746	<0.001	[0.609, 0.943]
Repair costs	ASM changes	0.367	0.033	[0.126, 0.706]
Repair costs	Flight Hours	0.014	0.812	—
Depreciation cost	fleet complexity	0.772	0.058	[0.069, 1.323]

Note: WCB is the two-sided p-value of the restricted Wild Cluster Bootstrap-t cluster by enterprise; Bootstrap is resampled 499 times for the entire enterprise.

3.2 Fixed-time out-of-sample evaluation

Table 3 reports the results for the fixed-time test period from 2022 to 2025. The RMSE of the multi-driver operating cost model is 0.0588, which is lower than that of the revenue model (0.0705), the ASM model (0.0653), and the unchanged model (0.0715). The out-of-sample RMSE of the operating cost model relative to the unchanged benchmark $R^2$is 0.323. The RMSE of the multi-driver fuel cost model is 0.2026, a decrease of 18.8% relative to the ASM model, and an out-of-sample RMSE of $R^2$0.266 relative to the unchanged benchmark. The Clark-West small-sample one-sided p-values for the operating cost and fuel cost models $t_{15}$are 0.024 and 0.007, respectively, and the bootstrap p-values for the cyclic block are 0.014 and less than 0.001, respectively.

The test periods for operating, fuel, personnel, and maintenance costs included 208, 190, 208, and 208 firm-quarter observations, respectively, while the test period for depreciation costs included 203 observations. When the historical mean replaced the unchanged baseline, the out-of-sample values for the multi-driver models for operating and fuel costs R^2 were 0.319 and 0.274, respectively. The model rankings obtained by replacing the baseline are consistent with those in Table 3, indicating that the predictive gain is not caused by a single baseline setting.

The personnel, maintenance, and depreciation models did not show equal gains. The personnel model had an RMSE of 0.1031, slightly higher than the unchanged baseline. The maintenance model only decreased by 0.43% relative to the ASM model, with a t_{15}one-sided p-value of 0.050, indicating that both the improvement in error and small-sample significance were within the margin. The depreciation model had an RMSE of 0.1403, higher than the unchanged baseline of 0.1360. These results do not support the conclusion that "adding variables can improve cost estimation." Only those variables that correspond to the drivers of the quantity-price formation process provide stable incremental information.

The bootstrap p-value for the cyclic block of the maintenance model was 0.036, but the absolute decrease in RMSE was only 0.0005, and the decrease in MAE was only 0.0004. The strength of evidence provided by statistical tests and error magnitudes is not the same. This study considers this result only as an exploratory gain and does not conclude from this that the multi-factor maintenance model has a stable budget advantage.

The MAE and RMSE rankings of the models are largely consistent, indicating that the advantages of the operating and fuel cost models are not entirely driven by a few large errors. The MAE of the operating cost multi-driver model is 0.0424, a decrease of approximately 10.0% from the ASM model's 0.0471. The MAE of the fuel cost multi-driver model is 0.0990, a decrease of approximately 34.6% from the ASM model's 0.1513. The MAE of the personnel model slightly increased from 0.0709 to 0.0710, while the depreciation model did not show a consistent improvement. Both error metrics support the fuel model, but neither supports the personnel and depreciation models. A comparison of fixed-time out-of-sample RMSE for different cost driver models is shown in Figure 1.

Table 3. Prediction Results of Conditions During Fixed-Time Testing Period

Cost items	No change	income	ASM	Multiple motivations	M2 MAE	OOSR^2	CWp value
Operating costs	0.0715	0.0705	0.0653	0.0588	0.0424	0.323	0.024
fuel costs	0.2364	0.2502	0.2495	0.2026	0.0990	0.266	0.007
personnel costs	0.1024	0.1180	0.1032	0.1031	0.0710	-0.015	0.314
Repair costs	0.1225	0.1301	0.1225	0.1220	0.0862	0.008	0.050
Depreciation cost	0.1360	0.1470	0.1404	0.1403	0.0780	-0.064	0.385

Note: OOS R^2uses zero cost change during the test period as a feasible benchmark; CW p-value is a one-sided test with 16 quarters and HAC lag of 3 periods t_{15}.

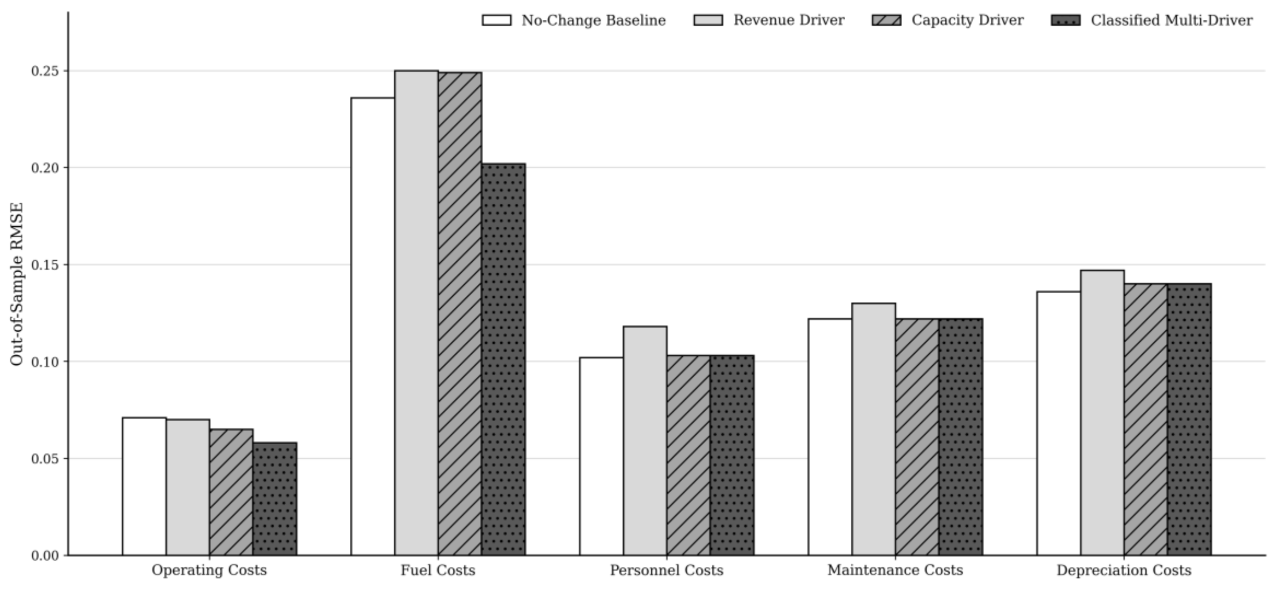

Figure 1. Comparison of fixed-time out-of-sample RMSE for different cost driver models.

3.3 Asymmetry, Period of Pressure, and Profitability

The complete M3 hierarchy shows that the coefficients for operating costs, fuel costs, personnel costs, maintenance costs, and depreciation $Down \times \Delta \ln ASM$are -0.017, 0.175, -0.039, 0.116, and -0.100, respectively, with all WCB p-values greater than 0.10. The triple interaction coefficients for fixed asset density are -0.046, 0.045, -0.093, -0.056, and -0.090, with corresponding p-values of 0.469, 0.839, 0.593, 0.788, and 0.114. Even after replacing the original variables with the proportion of fixed assets to total assets, the five triple interactions remain insignificant. Both asset definitions yielded consistent conclusions, and the sample does not support the notion that fixed asset structure generally strengthens cost stickiness in classification.

The error during the stress period exhibits a different model ranking compared to the normal testing period. In 2020-2021, the RMSE of the fuel multi-factor model was 0.3446, significantly lower than the unchanged baseline of 0.8733, and the maintenance model was also lower than the unchanged baseline. The RMSEs of the operating, personnel, and depreciation multi-factor models were 0.2229, 0.3926, and 0.3742, respectively, all higher than their corresponding unchanged baselines. The cost formation mechanism during the pandemic may have structural discontinuities; this study only reports prediction errors and does not make causal inferences regarding the stability of the mechanism.

Other robustness tests further distinguished between stable and boundary evidence. After 1% tailing, the coefficients for fuel consumption and real price were 0.689 and 0.735, respectively, with corresponding WCB p-values of 0.004 and less than 0.001, indicating that fuel price exposure remained significant. In 499 firm block bootstraps, none of these three coefficients crossed zero in 95% of the intervals. When the minimum historical period was changed to 16 or 32 quarters, the fuel quantity coefficient ranged from 0.653 to 0.770, and the real price coefficient ranged from 0.697 to 0.749. Maintenance ASM and depreciation complexity maintained their original directions under some definitions, but their tailed WCB p-values were 0.063 and 0.112, respectively. This study considers the latter two results as boundary relationships rather than deterministic drivers.

When the sample excludes 2020-2021, the ASM coefficient for operating costs is 0.316, and the WCB p-value is 0.028; the fuel price exposure coefficient is 0.779, and the p-value is 0.003. The normal sample still supports the relationship between size and price exposure, but the coefficients for the normal sample differ from those for the full sample. This difference suggests that the same parameter should not be used to interpret periods of stress and periods of normalcy.

Table 4 Conditional Relationship between Unit Cost and Operating Profit Margin by Category

Classification of unit costs	Concurrent coefficient	WCBp value during the same period	Lagged coefficient	Lag WCBp value
fuel	-1.775	0.644	6.074	0.171
Flight personnel	-22.822	0.121	2.846	0.638
repair	-10.805	0.316	-4.420	0.707
depreciation	-4.704	0.725	4.914	0.475
Joint inspection	—	0.451	—	0.804

Note: The dependent variable is the change in operating profit margin; the observations for the same-period and lagged models are 687 and 672, respectively.

Regression analysis of unit costs by category during the same period shows that the unit cost coefficients for fuel, personnel, maintenance, and depreciation are -1.775, -22.822, -10.805, and -4.704, respectively, with corresponding WCB p-values of 0.644, 0.121, 0.316, and 0.725, and a joint p-value of 0.451. The bias of the same-period model relative to the firm and quarterly fixed-effects benchmark $R^2$is 0.294. In the lagged-period model, the four coefficients show inconsistent directions, with a joint p-value of 0.804 and a bias $R^2$of only 0.022. The difference between the same-period and lagged results indicates that the same-period fit mainly reflects the accounting conditional relationship between unit costs and profit margins within the reporting period, and this result cannot be interpreted as a stable inter-period profitability effect. The conditional relationship between category unit costs and operating profit margins is shown in Table 4.

4. Discussion

this study is that classification drivers can only provide stable cost information when they are matched with the resource consumption process. Fuel costs are formed by the quantity consumed and external prices, and revenue or ASM cannot replace purchase price information. The short-run arc elasticity of actual fuel prices is less than 1, which may be related to purchase contracts, inventory valuation and settlement lag. Existing studies have also found that ticket prices do not immediately adjust to fuel shocks [11]. Public data cannot identify hedging positions and their reporting positions, so this study cannot directly attribute fuel price coefficients to hedging.

Fuel costs were relatively stable, but why did other cost categories not show the same performance? The granularity of the publicly available data can explain some of the differences. Personnel costs are constrained by seniority wages, guaranteed working hours and shift scheduling, maintenance costs also depend on overhaul events, outsourcing contracts and spare parts consumption, and depreciation is related to fleet retirement and asset disposal arrangements [12]. The publicly available quarterly tables do not fully disclose this information, and increasing the financial ratio cannot replace contract and event data. Neither the full-level M3 nor the alternative asset caliber supports the general strengthening of cost stickiness by fixed asset density. This result suggests that researchers must explain the interaction terms under the condition of complete main effects and low-order interactions. The fixed asset density coefficient reflects the marginal effect of structural conditions, and it does not represent short-term dynamic elasticity [13-16].

Even after a model demonstrates statistical correlation, managers still need to determine its budgetary value. Improvements in the operating and fuel models are supported by both error magnitude and small-sample testing, while the improvement in the maintenance model is minimal and insufficient to establish a stable management advantage. Some models exhibit error ranking reversals during periods of stress, indicating that unusual shocks may alter resource utilization and cost recognition processes. Quarterly differencing only reflects adjustments between adjacent quarters; managers cannot directly multiply short-term arc elasticity by four and apply it to the annual budget. Long-term analysis requires the use of additional annual panel, distributed lag, or four-quarter rolling models [17-20].

How cost drivers are incorporated into profitability analysis also requires a clear definition of the evidentiary boundaries. Profitability regression reveals conditional relationships, not causal effects. While the negative direction of the contemporaneous coefficient aligns with accounting relationships, cluster inference is unstable and lagged information is weak. Therefore, the categorical driver model is suitable for budget decomposition and variance attribution, but it cannot prove that cost changes have sustained profitability consequences. Companies can use M0, M1, and M2 as revenue proportions, core business volume, and categorical driver budgets, respectively, and determine whether to include these parameters in the formal budget based on out-of-sample error over a fixed time period. Companies should classify fuel prices as external market variances and fuel consumption as operational efficiency variances; they should also combine contract, scheduling, and work order data to determine personnel and maintenance responsibilities [21-24].

this study are still limited by the sample scope and information granularity. The study sample only includes large US airlines, and publicly available data does not allow for observation of internal budgeting systems, labor contracts, maintenance work orders, and hedging arrangements. The test period used drivers that had already been realized or were given in the budget during the same period, and this setting is not equivalent to ex-ante forecasting under unknown business volume conditions. Future research could access corporate planned values and event logs to examine the applicability of categorized drivers in rolling forecasting and long-term profit and loss management [25-30].

5. Conclusion

This study yielded four interrelated conclusions. First, operating revenue is not a universal driver of all costs. The mechanistic multi-driver model, relative to revenue and the ASM model, only shows stable out-of-time sample gains for operating costs and fuel costs. Second, fuel consumption and actual prices are the most robust categorical drivers. Evidence regarding maintenance capacity and fleet complexity is sensitive to outlier handling, while personnel cost analysis requires internal contracts and scheduling information. Third, neither the complete hierarchical model nor the alternative asset caliber supports the notion that fixed asset density universally enhances cost stickiness; therefore, structural variable coefficients should not be interpreted as short-term dynamic elasticities. Fourth, the contemporaneous direction of categorical unit costs and operating profit margins conforms to accounting relationships, but individual and joint tests are insignificant, and lagged information is weaker. Researchers cannot extrapolate causality or long-term profitability based on these coefficients.

The above conclusions support large enterprises shifting their profit and loss management from a uniform revenue-expense ratio to a hierarchical analysis of "categorized costs—corresponding drivers—conditional forecasts—profit outcomes." Before using the model for budgeting and performance evaluation, enterprises should simultaneously examine the rationality of the driver mechanism, whether the model has a fixed-time out-of-sample gain, and whether the model is stable during periods of stress. Enterprises should also define responsibility boundaries based on price, efficiency, asset structure, and resource commitments.

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