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Financial Sustainability of European Air Navigation Service Providers and the Impact of the COVID-19 Pandemic

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Abstract

This study examines the financial resilience of European Air Navigation Service Providers (ANSPs) before and after the COVID-19 shock. Using a balanced panel dataset covering 2017–2023 for over 30 ANSPs, we employ fixed-effects estimators to quantify changes in key financial metrics—revenue, operating costs, capital expenditures, and free cash flow—once air traffic volumes collapsed. Our findings reveal a pronounced downturn in profitability and liquidity in 2020, followed by uneven recovery trajectories across providers. We also identify factors—such as pre-pandemic leverage and cost structure—that moderated the depth of the shock. These insights contribute to crisis-management literature in aviation finance and offer policy implications for bolstering sectoral sustainability against future disruptions.

1. Introduction

The smooth operation of modern air transport critically depends on Air Navigation Service Providers (ANSPs), which coordinate enroute and terminal air traffic across national boundaries. As monopolistic, capital-intensive entities, ANSPs recover costs through user charges calibrated to forecast traffic volumes. Under stable demand, this framework balances infrastructure investment with operational expenses; however, it inherently exposes providers to volume fluctuations and external shocks.

The COVID-19 pandemic represented an unprecedented demand shock: between March and May 2020, European air traffic plunged by 72.8 % compared to the previous year (Total of Total Network Manager Area (All flights) over March 1st to May 31st compared between 2020 and 2019), eliminating a large share of enroute charges (EUROCONTROL, 2025). Unlike airlines, which could ground fleets or renegotiate leases, ANSPs maintained continuous service obligations—yet their revenue base evaporated, with documented steep cash-flow contractions for individual providers such as Nav Canada and European Air Navigation Service Providers (Carey, 2020; EUROCONTROL, 2021), but a comprehensive, cross-provider analysis of financial resilience during this period remains lacking. In particular, the roles of pre-pandemic leverage, fixed-cost structure, and national policy support in moderating the depth and duration of the crisis have not been systematically quantified.

This paper fills that gap by employing a balanced panel dataset of over 30 European ANSPs spanning 2017–2023. Using fixed-effects estimators and robustness checks (including random-effects and system GMM specifications), we assess how key financial indicators—revenue, operating costs, capital expenditures, and free cash flow—responded to the COVID-19 shock and subsequent recovery efforts. Our contributions are threefold: (1) we provide the first large-scale, panel-level evidence on ANSP financial sustainability under stress; (2) we identify structural factors (e.g., leverage ratios, cost composition) that enhanced or undermined resilience; and (3) we derive policy implications for reinforcing ANSP stability against future disruptions. These insights will inform regulators, policymakers, and service providers seeking to bolster the sector's crisis-management capabilities.

2. Literature Review

Financial sustainability stems from the capability to absorb, adapt to, and recover from economic shocks (Broto and Lamas, 2020; Chen and Sun, 2024). Adaptability is a key element to reach sustainability, and the level of an organization's or an ecosystem's adaptability may even lead to benefit from the shocks, or it may stay unaffected, recover from, or reconfigure itself after the shock (Gallopin, 2006;

Salignac et al., 2019). Which of these consequences would prevail depends on the internal and external resources available to organizations, and moderating impacts of an organization's resources needs to be included in assessments of financial sustainability.

Ensuring sustainability and resilience of the aviation industry against systemic disruptions is critical not only for the industry itself, but due to the cascading potential impacts on other industries such as transportation, storage, postal service, and wholesale and retail trade. While some systemic disruptions were short-lived such as the Blue Screen of Death (BSOD) crisis (albeit very disruptive), long-term disruptions such as Covid-19 pandemic led to stark financial struggles for all parts of the aviation industry (Venkata, 2025; Zhou and Zhang, 2024). Due to these consequences, analysis of financial resilience of the aviation industry is of paramount importance in management and policy frameworks to withstand different types of disasters, which is associated with achieving resilience (Rose, 2004; Handmer et al., 1996).

In the recent past, the aviation sector has experienced economic downturns due to pandemics, wars, terrorist attacks, and financial crises (Bilotkach et al., 2015; Caprian, Lom and Caprian, 2023; Ölçen and Alnıpak, 2023; Tuncal, 2025). Before Covid-19 pandemic, disasters and crises such as Gulf War, Asian Financial Crisis, 9/11 attacks, and severe acute respiratory syndrome (SARS) epidemic had caused significant decreases in the demand for air travel. Furthermore, there were significant shifts in consumer attitude, moving away from business and first-class seats (Mason, 2005). All these changes resulted in the revenues for airlines dropping, and therefore a decrease in the revenues of organizations on whom the airlines rely on to provide their services.

Following the Second World War, the states established Air Navigation Service Providers (ANSPs) to exercise authority over and regulate airspace above their sovereign territory. While airlines and airports operate in very competitive market conditions, for ANSPs, service provision today largely remains within national monopolies, facing minimal competitive pressure and demonstrating limited commercial focus (Efthymiou, 2023). ANSPs are responsible for air traffic management, communication, navigation and surveillance, meteorological services, search and rescue services, and aeronautical information management under a vertically integrated structure (Abeyratne, 2012; Schmitt et al., 2016). Due to their structure, they incur high fixed costs while maintaining a high level of safety and security standards (Papavramides and Molinari, 2002). On the other hand, most Air Navigation Service Providers (ANSPs) are funded through two main approaches: direct revenue from user charges and indirect support via government budgets or dedicated funds. Globally, the majority of ANSPs rely on a mix of user fees and supplementary funding sources to finance their operations (Tomová, 2016).

With the user charges being their major revenue source, ANSPs can cause between 5% and 10% of an airline's operating expenses (Quendt et al., 2007). Furthermore, the fragile cost structure of ANSPs requires them to increase user charges when demand for their services falls (due to high fixed costs). However, this would leave users of ANSPs, which include airlines, in a dire situation where their own revenues fall deeply, and their costs increase dramatically at the same time. Moreover, before the Covid-19 pandemic, there was limited standardization of equipment, slow uptake of new technologies, and less collaboration among national ANSPs than anticipated (Blondiau et al., 2016). The Covid-19 pandemic created circumstances of profound damage to the financial status of users of ANSPs and hence to ANSPs themselves.

The outbreak of COVID-19 led to a near-total halt in air travel because of widespread travel bans, quarantine measures, and lockdowns that impacted nearly half of the global population. Most airlines cut their flight operations by over 90%, with some ceasing operations altogether (Michelmann et al., 2023). There has been a certain level of research done on the impacts of pandemics and similar health crises situations on the aviation industry prior to the Covid-19 pandemic (Gold et al., 2019); however, Covid-19 proved to be unprecedented in terms of severity. Whereas earlier epidemics such as SARS, MERS and Ebola (1991–2019) prompted studies on airport hygiene, travel restrictions and contagion modelling, and regionally limited disruptions like SARS in Hong Kong caused notable but localized impacts, none came close to the global shutdown induced by COVID-19—when air travel nearly vanished worldwide, passenger traffic plunged over 60%, and losses exceeded $126 billion in a single year (Kamat and Li, 2024; Kazda et al., 2022; Linden, 2021; Liu et al., 2021).

Prior to the Covid-19 pandemic, ANSPs experienced modest profitability, averaging approximately 0.3% in economic profit between 2012 and 2019. Considering their role in forming the foundational infrastructure relied on by airlines and air travel services, financial sustainability of ANSPs is needed to be ascertained (Arblaster, 2018; Materna, 2019). Because ANSPs' revenues are largely variable and dependent on aircraft activity, they incurred substantial losses during Covid-19 in 2020 (Bouwer et al., 2022). While a growing body of literature has emerged in response to the impacts of COVID-19 on airlines and airports (Suau-Sanchez et al., 2020; Suau-Sanchez et al., 2021; Fontanet-Pérez et al., 2024), there remains a notable empirical gap when it comes to Air Navigation Service Providers (ANSPs).

The literature on post-crisis financial sustainability in the aviation sector has expanded notably since the COVID-19 outbreak. Abdi, Li, and Càmara-Turull (2023), drawing on a synthesis of 173 peer-reviewed contributions, found that while environmentally oriented ESG policies may increase cost burdens in certain contexts, socially and governance-driven practices tend to cushion financial shocks and strengthen organisational resilience. Methodological advances have also emerged; Le Gallo and Sénégas (2023) contend that the traditional "quasi-demeaned" calculation of the Hausman statistic can be unreliable in the presence of heteroskedasticity, recommending instead the application of Feasible Generalised Least Squares (FGLS)-based variance estimates to improve the robustness of panel data estimations. Complementing these broader insights, case study analysis by Cao, Wang, and Zhao (2024) illustrates how carriers such as HNA Group and Aegean Airlines adopted post-pandemic measures—including targeted fleet downsizing, enhanced operational agility, and strategic workforce adjustments—that collectively reduced exposure to financial vulnerability during the recovery stage.

Most existing studies focus on operational or policy-level responses in the broader aviation sector, with limited attention to the financial performance and resilience of ANSPs during the crisis. There is a lack of financial panel data analyses that examine how ANSPs were affected across different regions and time periods. Furthermore, few studies investigate the heterogeneity in ANSPs' responses or the role of moderating factors such as pre-crisis financial leverage, institutional governance structures, or funding models. This gap highlights the need for more targeted, empirical research to understand the financial dynamics and structural vulnerabilities within this critical yet understudied subsector of aviation, which is the purpose of this study.

3. Methodology

3.1. Data and Variable Definitions

We build a balanced panel of 32 European ANSPs over the 2017–2023 period. Our primary dataset (“ansp_panel_data”) contains annual observations on:

Revenue (revenue): Total enroute and terminal charges (million EUR),

Operating Expenditure (opex): Total operating costs (million EUR),

Capital Expenditure (capex): Investment in fixed assets (million EUR),

Free Cash Flow (fcf): Net cash after operations and CAPEX (million EUR),

Total Liabilities (tot_liab): Sum of current and non-current liabilities (million EUR),

Control Variables: Pre-pandemic leverage (tot_liab/revenue), traffic volume proxy, and a post-COVID dummy (post_covid, =1 if year ≥ 2020).

All monetary variables are converted to constant 2017 euros using annual GDP deflators to remove inflation effects. Continuous variables are log-transformed (e.g., ln(revenue)) to mitigate skewness.

3.2. Model Specification

To isolate the COVID-19 shock and control for time-invariant heterogeneity, we estimate:

$$ln(Y_{it}) = \alpha_i + \gamma_t + \beta_1 PostCovid_t + \beta_2\, ln(Capex_{it}) + \beta_3 ln(Opex_{it}) + \beta_4 Levi_{i,t-1} + \varepsilon_{it} \quad (1)$$

Table 1. Variable Definitions and Notation

Notation	Definition
Y_{it}	Revenue (or financial performance) of ANSP *i* in year *t*
α_i	Unit (country/provider) fixed effect
γ_t	Year fixed effect (time FE)
$PostCovid_t$	Dummy variable for the post-COVID period (1 if year ≥ 2020, 0 otherwise)
$Capex_{it}$	Logarithm of capital expenditures for ANSP *i* in year *t*
$Opex_{it}$	Logarithm of operating expenditures for ANSP *i* in year *t*
$Levi_{i,t-1}$	Leverage ratio of ANSP *i* lagged by one year
ε_{it}	Error term

We estimate separate regressions for each dependent variable (revenue, fcf, etc.) to trace differential impacts.

3.3. Estimation Strategy

Fixed-Effects (FE) Estimation: Primary approach to eliminate α_i bias from time-invariant unobservables (Wooldridge, 2010),

Random-Effects (RE) Model: Conducted as a robustness check; Hausman test determines preferred specification (Hausman, 1978),

System GMM: For potential endogeneity of capex and opex, we implement a two-step System GMM following Blundell and Bond (1998), using lags as instruments and Windmeijer (2005) finite-sample correction for standard errors.

All estimations employ heteroskedasticity-robust and cluster-robust (by provider) standard errors to account for serial correlation and cross-sectional dependence.

3.4. Diagnostic Tests and Robustness Checks

Hausman Test: Compare FE vs. RE; reject RE if $p < 0.05$, confirming FE validity, The Hausman test statistic ($\chi^2 = 23.82$, $p < 0.001$) strongly rejects the null hypothesis of no systematic difference between the FE and RE estimators, confirming that provider-specific unobserved heterogeneity is correlated with the explanatory variables. Therefore, the fixed-effects estimator is preferred for the baseline specification.

Breusch–Pagan Lagrange Multiplier: Test for random-effects variance component,

Wooldridge Test: Detect first-order autocorrelation in panel residuals (Wooldridge, 2010),

Pesaran CD Test: Check cross-sectional dependence in residuals (Pesaran, 2021),

Unit-Root Checks: Levin–Lin–Chu test to ensure stationarity of key series, and finally, we exclude potential outliers (top/bottom 1% revenue) to verify robustness.

To ensure the robustness and validity of our panel estimations, we conducted a comprehensive suite of diagnostic tests. These include checks for model specification, serial correlation, cross-sectional dependence, and stationarity. The results, presented in Appendix Tables A1–A5, support the use of fixed-effects estimation and confirm that inference procedures are properly adjusted for key econometric concerns.

4. Findings

Table 2 on the next page presents the descriptive statistics for the main financial indicators of European Air Navigation Service Providers (ANSPs) over the period 2017–2021. The analysis covers 145 firm-year observations.

Revenue displays a mean of approximately 970.1 million EUR, with a standard deviation of 1,381.6 million, indicating substantial variability in income across ANSPs and years. The minimum recorded revenue is just under 4 million EUR, while the maximum reaches 6.85 billion EUR, reflecting significant size differences among European providers.

Operating expenses (OPEX) average at -806.1 million EUR (standard deviation: 1,049.8 million), with values ranging from -4.73 billion EUR to roughly -1.74 million EUR. The consistently negative sign is expected, as OPEX represents outgoing cash flows. The large spread suggests both scale effects and differing cost structures. EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization) has a mean of 164.0 million EUR, but with considerable dispersion (SD: 540.9 million). Values range from -1.1 billion EUR to 3.48 billion EUR. The negative minimum signals the presence of loss-making years for some providers, especially in crisis periods.

Depreciation averages at -127.7 million EUR, ranging from -1.13 billion to -0.52 million, reflecting capital intensity and infrastructure investment cycles in the sector. Total liabilities (mean: 803.3 million EUR; SD: 1,565.5 million) vary widely, with some providers maintaining a very high leverage (up to 10.04 billion EUR) and others operating with much lower debt levels.

Cash and equivalents average 448.9 million EUR, but with high variability (SD: 1,053.6 million), suggesting uneven liquidity positions. Cash days (mean: 153.3; SD: 141.6) show some firms with essentially zero cash reserves and others able to cover over two years of expenses from cash on hand. Net operating profit averages 142.6 million EUR (SD: 515.1 million), with a minimum of -1.51 billion and a maximum of 2.95 billion, showing that operational profitability is highly sensitive to traffic volume and crisis effects.

Other indicators, such as net investment (mean: -113.0 million), net financing flows (mean: -46.1 million), and net cash flow (mean: -16.5 million), further highlight the financial stress and investment patterns observed in the sector during the sample period. Capital expenditures (CapEx) average at -132.2 million EUR (min: -1.11 billion; max: 0), reflecting persistent investment, while free cash flow (FCF) has a modest mean of 10.4 million EUR but with high standard deviation, indicating volatile financial performance.

Overall, the data reveal extreme heterogeneity among European ANSPs, both in size and in their financial resilience. The wide dispersion in revenues, costs, liquidity, and investment indicators underscores the divergent impact of external shocks (such as the COVID-19 pandemic) across the sector. This variation will be further examined in the following regression and panel data analyses to identify key determinants of financial sustainability.

Table 3 on the next page displays the Pearson correlation coefficients among the key financial variables for European ANSPs between 2017 and 2021. Several noteworthy patterns emerge from the data.

Table 2. Descriptive Statistics of Key Financial Indicators for European ANSPs (2017–2021)

Variable	Obs	Mean	Std. Dev.	Min	Max
Revenue	145	970.13	1.381.59	3.94	6.845.37
OPEX	145	-806.09	1.049.80	-4.731.13	-1.74
EBITDA	145	164.04	540.86	-1.097.15	3.482.84
Depreciation	145	-127.72	221.80	-1.130.64	-0.52
Total Liab.	145	803.27	1.565.55	2.14	10.044.00
Cash Eq.	145	448.95	1.053.58	0.00	5.647.00
Cash Days	145	153.33	141.57	0.00	775.99
Net Op. Prof.	145	142.59	515.07	-1.510.91	2.954.19
Net Invest.	145	-113.00	284.86	-1.147.05	1.270.73
Net Finance	145	-46.06	416.75	-2.005.77	1.419.35
Net CF	145	-16.48	453.98	-4.164.40	2.266.85
CapEx	145	-132.16	213.99	-1.105.21	0.00
FCF	145	10.42	474.60	-2.233.35	2.713.43

Note: All monetary values are in millions of EUR. OPEX and depreciation are reported as negative values due to their accounting nature.

Table 3. Pearson Correlation Matrix of Main Financial Indicators

	revenue	opex	ebitda	depr	tot_liab	cash_eq	cash_days	net_op	net_inv	net_fin	net_cf	Capex	fcf
Revenue	1.00	-0.94*	0.74*	-0.81*	0.46*	0.72*	0.34*	0.70*	-0.60*	-0.27*	0.17*	-0.78*	0.40*
Opex		1.00	-0.45*	0.79*	-0.52*	-0.66*	-0.27*	-0.46*	0.65*	0.16	0.03	0.84*	-0.13
Ebitda			1.00	-0.54*	0.16	0.55*	0.34*	0.88*	-0.26*	-0.38*	0.48*	-0.36*	0.79*
Depr				1.00	-0.23*	-0.40*	-0.10	-0.42*	0.69*	0.10	0.05	0.80*	-0.09
tot_liab					1.00	0.75*	0.54*	0.29*	-0.37*	-0.08	0.02	-0.43*	0.12
cash_eq						1.00	0.76*	0.65*	-0.36*	-0.33*	0.21*	-0.46*	0.50*
cash_days							1.00	0.48*	-0.05	-0.34*	0.20*	-0.15	0.46*
net_op								1.00	-0.24*	-0.42*	0.60*	-0.39*	0.91*
net_inv									1.00	-0.27*	0.11	0.78*	0.09
net_fin										1.00	0.27*	0.14	-0.39*
net_cf											1.00	0.17*	0.73*
Capex												1.00	0.03
Fcf													1.00

Note: * indicates statistical significance at the 5% level.

First, revenue shows a strong negative correlation with operating expenses (OPEX) ($r = -0.94$, $p < 0.05$), as expected, since higher revenues typically co-occur with higher costs but in opposite directions due to accounting conventions. Revenue is also highly positively correlated with EBITDA ($r = 0.74$, $p < 0.05$) and cash and equivalents ($r = 0.72$, $p < 0.05$), indicating that larger ANSPs are not only more profitable but also tend to maintain higher liquidity.

EBITDA is strongly associated with net operating profit ($r = 0.88$, $p < 0.05$), reinforcing its role as a key measure of operational performance. A notable positive correlation between total liabilities and cash and equivalents ($r = 0.75$, $p < 0.05$) suggests that more leveraged firms also tend to hold larger cash reserves—possibly as a buffer against financial risks or volatility in traffic volumes.

Net investment and capex are highly correlated ($r = 0.78$, $p < 0.05$), as expected, reflecting the capital-intensive nature of ANSP operations. Free cash flow (FCF) is most closely tied to net operating profit ($r = 0.91$, $p < 0.05$) and net cash flow ($r = 0.73$, $p < 0.05$), highlighting that operational profitability is the main driver of cash generation in the sector.

It is also noteworthy that several variables exhibit significant negative correlations. For example, capex is negatively correlated with revenue ($r = -0.78$, $p < 0.05$) and net operating profit ($r = -0.39$, $p < 0.05$), suggesting that periods of intensive capital investment are often associated with lower short-term profitability or during times of external stress (such as during the COVID-19 pandemic).

Overall, the correlation matrix highlights the tight interdependence of financial performance, liquidity, and investment among European ANSPs. These relationships underscore the need to control for multicollinearity in subsequent regression models, especially when analyzing the determinants of financial sustainability.

Table 4 in the next page reports the results of the fixed effects panel regression examining the determinants of revenue for European ANSPs from 2017 to 2021. The model controls for firm-level unobserved heterogeneity and year effects. As expected, operating expenses (OPEX) are highly significant and negatively associated with revenue (coef = -0.88, $p < 0.001$), confirming the direct impact of cost structure on top-line performance. The coefficient indicates that, holding other factors constant, an increase of 1 million EUR in OPEX is associated with a decrease of approximately 0.88 million EUR in revenue, highlighting the close operational linkage between expenditure and revenue generation in the ANSP sector.

Cash and equivalents emerge as a highly significant positive predictor (coef = 0.94, $p < 0.001$), suggesting that firms with higher liquidity are better positioned to sustain or grow their revenues, likely due to enhanced resilience during external shocks or the ability to seize operational opportunities.

Table 4. Fixed Effects Regression Results for Revenue Determinants (2017–2021)

Variable	Coefficient	Std. Error	t	p-value	95% CI
OPEX	-0.878	0.154	-5.70	0.000	-1.184 ; -0.572
Depreciation	-0.562	0.820	-0.68	0.495	-2.189 ; 1.065
Tot. Liab.	-0.062	0.093	-0.67	0.503	-0.246 ; 0.122
Cash Eq.	0.937	0.093	10.06	0.000	0.752 ; 1.121
CapEx	-0.571	0.341	-1.67	0.097	-1.248 ; 0.106
Year 2018	-17.154	66.553	-0.26	0.797	-149.176; 114.869
Year 2019	-98.824	68.550	-1.44	0.153	-234.809; 37.161
Year 2020	-135.225	72.901	-1.85	0.067	-279.840; 9.390
Year 2021	380.894	164.174	2.32	0.022	55.217 ; 706.570
Constant	-207.892	143.522	-1.45	0.151	-492.600; 76.816

Model summary: Number of observations: 145, Number of groups: 35, Within R^2: 0.697, $F(9,101) = 25.82$; Prob > F = 0.000, Variance due to unit effects (rho): 0.87

Other explanatory variables, such as depreciation, total liabilities, and capital expenditures (CapEx), are not statistically significant at conventional levels, although CapEx displays a negative association with revenue at the 10% significance threshold ($p = 0.097$). This finding may reflect a short-term trade-off, where periods of elevated investment are associated with lower immediate revenue, possibly due to construction works or operational disruptions.

Regarding time effects, only the 2021 dummy is statistically significant (coef = 380.89, $p = 0.022$), indicating a notable rebound in revenues post-pandemic, relative to the base year (2017). This result is consistent with the broader industry recovery observed after the severe contraction in 2020.

The overall model fit is robust (within $R^2 = 0.697$), and the significant F-test (Prob > F = 0.000) confirms the joint explanatory power of the included variables. The high rho value (0.87) indicates substantial cross-sectional heterogeneity among ANSPs, justifying the use of fixed effects.

In summary, the analysis highlights the central role of cost management and liquidity in driving revenue among European ANSPs, while also revealing the uneven recovery trajectories across years. These results provide important empirical support for the subsequent risk and policy analyses.

To assess potential multicollinearity among the explanatory variables, the variance inflation factor (VIF) was calculated for each regressor in the main specification (see Table 5 above). All VIF values are well below the commonly used threshold of 10, with the highest value (OPEX) at 5.89 and a mean VIF of 2.95. This result indicates that multicollinearity is not a serious concern in the model, and the estimated coefficients can be interpreted with confidence. Similar findings have been reported in recent panel data studies involving firm-level financial metrics.

Table 5. Variance Inflation Factors (VIF) for Main Regression Variables

Variable	VIF
OPEX	5.89
CapEx	4.63
Depreciation	4.01
Cash Eq.	3.36
Total Liab.	2.83
Year 2020	1.57
Year 2018	1.52
Year 2019	1.52
Year 2021	1.20
Mean VIF	**2.95**

To ensure the validity of the panel regression results, the model was re-estimated using cluster-robust standard errors, with clustering at the country (ANSP) level (see Table 6 on the next page). The main findings remain qualitatively unchanged. Operating expenses (OPEX) and cash and equivalents continue to exhibit strong and statistically significant associations with revenue ($p < 0.001$ for both), although standard errors are now larger, reflecting the adjustment for potential intra-group correlation and heteroskedasticity.

Other variables—including depreciation, total liabilities, and capital expenditures—remain statistically insignificant, and time fixed effects (year dummies) largely do not alter the main conclusions. The significant association for OPEX (coef = -0.88, $p < 0.001$) and cash and equivalents (coef = 0.94, $p < 0.001$) confirms the robustness of the primary results, even under more stringent error assumptions.

These results indicate that the model is robust to violations of classical error assumptions, lending greater confidence to the empirical findings. Robust standard errors are commonly recommended in recent panel data literature to address issues of heteroskedasticity and autocorrelation within clusters.

As an additional robustness check, the fixed effects panel regression was re-estimated using Driscoll-Kraay standard errors, which are robust to general forms of cross-sectional dependence, heteroskedasticity, and serial correlation (see Table 7 on the next page). The primary findings are qualitatively unchanged and remain statistically significant at conventional levels. Operating expenses (OPEX) retain a strong and negative association with revenue (coef = -0.88, p = 0.024), underscoring the pivotal role of cost control in shaping ANSP financial performance. Similarly, cash and equivalents remain a highly significant and positive predictor (coef = 0.94, p = 0.002), supporting the notion that liquidity is critical for sustaining revenue generation, particularly during periods of external shock or market uncertainty.

Time effects indicate that 2019 and 2020 were characterized by significant revenue declines compared to the baseline year (2017), in line with the onset and impact of the COVID-19 pandemic. The 2021 dummy, while positive, is not statistically significant at the 5% threshold, possibly reflecting an incomplete or uneven sectoral recovery.

Table 6. Fixed Effects Regression Results with Cluster-Robust Standard Errors

Variable	Coefficient	Robust SE	t	p-value	95% CI
OPEX	-0.878	0.185	-4.76	0.000	-1.253 ; -0.503
Depreciation	-0.562	0.985	-0.57	0.572	-2.565 ; 1.441
Tot. Liab.	-0.062	0.201	-0.31	0.758	-0.470 ; 0.346
Cash Eq.	0.937	0.129	7.26	0.000	0.674 ; 1.199
CapEx	-0.571	0.469	-1.22	0.232	-1.525 ; 0.383
Year 2018	-17.154	37.224	-0.46	0.648	-92.802; 58.494
Year 2019	-98.824	78.890	-1.25	0.219	-259.148; 61.500
Year 2020	-135.225	79.752	-1.70	0.099	-297.301; 26.851
Year 2021	380.894	282.075	1.35	0.186	-192.351; 954.138
Constant	-207.892	142.738	-1.46	0.154	-497.971; 82.186

Table 7. Fixed Effects Regression with Driscoll-Kraay Standard Errors

Variable	Coefficient	DK Robust SE	T	p-value	95% CI
OPEX	-0.878	0.249	-3.53	0.024	-1.569 ; -0.187
Depreciation	-0.562	1.348	-0.42	0.698	-4.303 ; 3.180
Tot. Liab.	-0.062	0.088	-0.71	0.519	-0.308 ; 0.183
Cash Eq.	0.937	0.133	7.05	0.002	0.568 ; 1.306
CapEx	-0.571	0.581	-0.98	0.381	-2.184 ; 1.042
Year 2018	-17.154	13.709	-1.25	0.279	-55.216; 20.908
Year 2019	-98.824	26.085	-3.79	0.019	-171.247; -26.400
Year 2020	-135.225	16.104	-8.40	0.001	-179.938; -90.513
Year 2021	380.894	194.734	1.96	0.122	-159.775; 921.562
Constant	-207.892	232.525	-0.89	0.422	-853.484; 437.699

Note: **Number of observations:** 145, **Number of groups:** 35, **Within R^2:** 0.697, **$F(9, 4) = 60.10$; $p = 0.0007$**

Table 8. Arellano-Bond Dynamic Panel Regression Results

Variable	Coefficient	Robust SE	Z	p-value	95% CI
L1. Revenue	-0.319	0.084	-3.80	0.000	-0.483 ; -0.155
OPEX	-0.929	0.146	-6.36	0.000	-1.216 ; -0.643
Depreciation	-0.518	1.044	-0.50	0.620	-2.563 ; 1.528
Tot. Liab.	-0.048	0.232	-0.21	0.836	-0.503 ; 0.407
Cash Eq.	1.078	0.153	7.05	0.000	0.778 ; 1.378
CapEx	-1.349	0.839	-1.61	0.108	-2.993 ; 0.295
Year_2 (2018)	-194.44	282.66	-0.69	0.492	-748.45; 359.57
Year_3 (2019)	-265.06	278.88	-0.95	0.342	-811.65; 281.53
Year_4 (2020)	-262.82	284.19	-0.92	0.355	-819.82; 294.17
Constant	70.47	411.05	0.17	0.864	-735.17; 876.11

Note: Obs: 75 | **Groups:** 35, **Number of instruments:** 16, **Wald $\chi^2(9)$:** 1212.45 | **Prob > χ^2:** 0.000

The stability of the key coefficients across estimation methods—including Driscoll-Kraay robust errors—reinforces the reliability of the core empirical results and minimizes concerns over model misspecification or unobserved cross-sectional dependence. The use of Driscoll-Kraay standard errors follows best practices in recent panel data literature for highly heterogeneous sectors (Driscoll & Kraay, 1998; Hoechle, 2007).

As a final robustness check, the model was estimated using the Arellano-Bond dynamic panel-data estimator, which addresses potential endogeneity and serial correlation by instrumenting lagged dependent variables and other regressors (see Table 8.). The results confirm the core findings from the static panel models. The coefficient on lagged revenue (L1.revenue) is negative and statistically significant (coef = -0.32, p < 0.001), suggesting a mean-reverting dynamic in ANSP revenues—years of high (or low) revenue tend to be followed by partial reversion toward the mean. This is consistent with the volatile and shock-prone nature of the aviation sector.

Consistent with earlier models, operating expenses (OPEX) maintain a strong and significant negative association with revenue (coef = -0.93, p < 0.001), while cash and equivalents remain a robust positive predictor (coef = 1.08, p < 0.001), highlighting the centrality of liquidity management. Other financial variables, including depreciation, total liabilities, and capital expenditures, do not reach conventional significance thresholds. Time effects for 2018–2020 (relative to the baseline year) are negative but not statistically significant, possibly reflecting high variability and the limited time-series dimension of the sample.

Diagnostic tests (not shown here, but available upon request) confirm the validity of the instrument set, with no evidence of instrument proliferation or overidentification. The use of Arellano-Bond GMM thus reinforces the reliability of the main findings and further alleviates concerns regarding endogeneity, dynamic bias, or autocorrelation in the panel setting (Arellano & Bond, 1991; Roodman, 2009).

Table 9. Panel Quantile Regression Results for Revenue Determinants

Variable	0.25 Quantile	(SE)	0.5 Quantile	(SE)	0.75 Quantile	(SE)
OPEX	-0.990	(1.020)	-0.868**	(0.433)	-0.806***	(0.236)
Depreciation	-0.863	(6.559)	-0.535	(2.769)	-0.369	(1.514)
Tot. Liab.	-0.176	(0.714)	-0.052	(0.305)	0.010	(0.165)
Cash Eq.	0.999	(0.989)	0.931**	(0.419)	0.897***	(0.229)
CapEx	-0.872	(2.851)	-0.544	(1.210)	-0.378	(0.659)
Year_2	-19.49	(236.25)	-16.95	(99.68)	-15.66	(54.54)
Year_3	-126.34	(255.40)	-96.39	(107.99)	-81.19	(58.91)
Year_4	-176.62	(299.33)	-131.56	(126.17)	-108.69	(68.82)
Year_5	328.90	(1520.70)	385.49	(641.89)	414.22	(351.08)

Note: Significance: *p < 0.1; **p < 0.05; ***, N = 145, balanced panel

Table 9. presents the results of the panel quantile regression for the 25th, 50th, and 75th percentiles of revenue among European ANSPs. The key insight is that the effects of core financial drivers—operating expenses (OPEX) and cash and equivalents—vary in magnitude across the conditional distribution of revenue. At all three quantiles, the coefficient on OPEX is negative, confirming that higher costs systematically erode revenue performance. However, statistical significance and the magnitude of the effect increase at higher quantiles: the OPEX coefficient is not significant at the 25th percentile but becomes significant at the median (coef = -0.87, p = 0.045) and highly significant at the 75th percentile (coef = -0.81, p = 0.001). This suggests that the adverse impact of operating costs is most pronounced for larger or more successful ANSPs.

Similarly, cash and equivalents show a positive association with revenue, significant at the median (coef = 0.93, p = 0.026) and especially at the upper quantile (coef = 0.90, p = 0.000). This result implies that maintaining higher liquidity buffers is particularly beneficial for firms operating at the top end of the revenue distribution, reinforcing the value of financial flexibility under conditions of operational or market stress. Other variables—including depreciation, total liabilities, and capital expenditures—do not display robust or statistically significant effects across quantiles. The lack of significance for time dummies and non-core financials may reflect structural similarities or persistent shocks (e.g., the pandemic) affecting all quantiles relatively uniformly.

Overall, the quantile regression analysis reveals substantial heterogeneity in the drivers of financial performance. For policymakers and managers, these findings highlight the importance of targeted cost control and liquidity strategies, especially for larger ANSPs that are more exposed to revenue volatility and operational scale effects.

5. Conclusion

This study provides a comprehensive panel data analysis of the financial sustainability of European Air Navigation Service Providers (ANSPs) between 2017 and 2021, covering the full shock cycle of the COVID-19 pandemic and its aftermath. By employing a wide range of econometric techniques—including fixed effects, robust and Driscoll-Kraay standard errors, dynamic panel (Arellano-Bond), and quantile regression—the research uncovers both central tendencies and distributional heterogeneity in the determinants of ANSP revenues.

The empirical findings consistently highlight the dominant roles of operating expenses and cash holdings in shaping revenue performance across models and quantiles. Higher operating costs erode revenues, with this effect becoming even more pronounced among higher-revenue

ANSPs. Conversely, increased liquidity not only supports operational resilience during external shocks but also delivers outsized benefits for firms at the upper end of the revenue spectrum. These relationships remain robust after accounting for potential endogeneity, serial correlation, and cross-sectional dependence. The dynamic panel analysis further reveals a significant mean-reverting pattern in ANSP revenues, reflecting the sector's exposure to cyclical shocks and its capacity for partial recovery following downturns. Quantile regression analysis emphasizes the asymmetric nature of financial risk in the sector, underscoring the importance of tailored strategies rather than blanket policy prescriptions.

Overall, the study demonstrates that financial sustainability in European air navigation is driven by both rigorous cost discipline and proactive liquidity management, especially in a volatile, crisis-prone environment. These insights hold direct implications for industry managers and policymakers aiming to strengthen sectoral resilience and foster long-term stability.

6. Policy Implications

The results of this analysis point to several actionable policy recommendations for European ANSPs, regulators, and sectoral stakeholders. Targeted Cost Control; given the amplified impact of operating expenses at higher revenue levels, ANSPs—particularly larger providers—should prioritize lean cost structures and strategic efficiency initiatives. Policymakers may consider benchmarking and incentivizing cost optimization programs across the sector.

Liquidity Buffers as Crisis Shields; the strong, positive effect of cash holdings on revenues, especially during periods of extreme volatility, suggests that minimum liquidity requirements or flexible reserve policies can materially enhance the financial sustainability of ANSPs. Regulatory frameworks should be adapted to allow greater latitude in building and deploying liquidity buffers, especially in anticipation of external shocks.

Risk-Sensitive Policy Design; the quantile regression results make it clear that a "one-size-fits-all" approach is insufficient. Policymakers should embrace risk-sensitive, differentiated policy measures that reflect the heterogeneous exposures and capacities of ANSPs across the revenue spectrum. Dynamic Stress Testing; the sector's mean-reverting revenue dynamics point to the value of dynamic, forward-looking stress testing frameworks that can identify potential vulnerabilities and inform pre-emptive mitigation strategies.

Data Transparency and Monitoring; continued emphasis on transparent, high-frequency financial data reporting will enable regulators to better monitor evolving risks and intervene early when necessary, promoting sector-wide stability. By implementing these evidence-based recommendations, European ANSPs and their regulators can better navigate future crises, sustain financial performance, and ensure the long-term provision of safe, reliable air navigation services across the continent.

The empirical analysis highlights how leading international airlines implemented post-pandemic financial sustainability measures to manage risks effectively. Three illustrative cases—Lufthansa Group, Singapore Airlines, and Delta Air Lines—demonstrate the diversity and effectiveness of these strategies.

Lufthansa Group pursued operational efficiency and financial resilience by modernizing its long-haul fleet. The share of four-engine aircraft was reduced from 50% to 15%, replaced by more fuel-efficient and environmentally friendly models. By 2024, the company planned to accelerate fleet renewal with the acquisition of new aircraft every ten days. These measures not only lowered operational costs but also reduced carbon emissions, reinforcing the company's post-crisis financial sustainability (lufthansagroup.com, aviacionline.com).

Singapore Airlines strengthened its financial position by issuing convertible bonds worth SGD 9.7 billion in 2021 and partially repaying them in 2022, securing essential liquidity. By 2024, the airline restored its passenger load factor to 87.1%, achieving pre-pandemic levels. These strategies demonstrate how proactive financial planning and risk management can facilitate recovery and maintain operational stability (singaporeair.com, asianaviation.com).

Delta Air Lines adopted multiple measures to stabilize its financial position. Streamlining fleet types increased operational efficiency, and temporarily deferring pension contributions improved cash flow. Consequently, the debt-to-EBITDA ratio declined to 2.8 by the end of 2022. Additionally, Delta regained an investment-grade rating from Fitch by 2024, highlighting the effectiveness of its post-crisis financial sustainability strategies (ir.delta.com, reuters.com).

These cases collectively illustrate that targeted fleet management, liquidity planning, and strategic cost control are critical components of risk management and financial sustainability in the international aviation sector after COVID-19.

7. Limitations

Despite the study's robust methodological framework and comprehensive dataset, several limitations warrant acknowledgement. Short Time Dimension; the analysis covers only five years (2017–2021), which, although sufficient to capture the COVID-19 shock, may limit the ability to generalize results to longer-term trends or to capture delayed adjustment effects.

Data Gaps and Aggregation; variation in reporting practices across European ANSPs may introduce measurement inconsistencies. Some relevant variables—such as non-core revenues or detailed capital structures—are not available for all providers. Model Specification Constraints; while multiple estimation techniques (FE, DK, GMM, quantile) were used to ensure robustness, small sample size and limited time periods may affect the precision of certain coefficient estimates, particularly in dynamic or quantile models. Unobserved Factors: the models focus on observable financial and operational metrics, potentially omitting important unobservable factors such as managerial quality, regulatory discretion, or external market linkages.

Future research should aim to expand the temporal and cross-country coverage, incorporate additional explanatory variables, and consider deeper institutional and operational drivers of ANSP financial performance.

Appendix

The test results are presented in the tables below

Appendix Table A1. Hausman Specification Test Results

Variable	FE Coefficient (b)	RE Coefficient (B)	Difference (b–B)	Std. Error
capex	0.0000998	0.0001544	–0.0000546	0.0000203
opex	–0.0001988	–0.0003449	0.0001462	0.0000314
tot_liab	0.0001656	0.0002281	–0.0000624	0.0000231
post_covid	–0.4732413	–0.4713487	–0.0018926	0.0040300
Test statistic (χ^2)	–	–	**23.82**	–
p-value	–	–	**0.0001**	–

The Hausman specification test strongly rejects the null hypothesis of no systematic differences between the fixed-effects (FE) and random-effects (RE) estimators ($p < 0.01$). This indicates that unobserved heterogeneity across ANSPs is likely correlated with the explanatory variables. Therefore, the FE estimator provides consistent and efficient estimates and is preferred for the baseline empirical specification. This finding supports the use of unit-specific fixed effects in modeling the financial drivers of European ANSPs.

Appendix Table A2. Breusch–Pagan Lagrange Multiplier Test for Random Effects

Component	Variance	Std. Dev.
ln_revenue	3.528	1.878
idiosyncratic error (e)	0.028	0.167
panel-level error (u)	1.414	1.189

Test statistic: chibar²(01) = 181.81, **p-value**: 0.0000

The LM test rejects the null hypothesis that there is no variance across ANSPs ($p < 0.001$), indicating that a panel model is preferred over simple pooled OLS. However, this result alone does not justify the use of the random-effects specification—in fact, when combined with the Hausman test (Appendix Table A1), which favors fixed effects, this result further supports the decision to use the fixed-effects model while accounting for unobserved provider-level heterogeneity.

Appendix Table A3. Wooldridge Test for First-Order Autocorrelation in Panel Data

Test Statistic	F(1, 34) = 7.667
p-value	0.0090

The Wooldridge test rejects the null hypothesis of no first-order autocorrelation at the 1% significance level. This suggests the presence of serial correlation in the panel error terms, which could bias standard errors if left uncorrected. To address this, the main estimations should incorporate robust or clustered standard errors and, when feasible, apply techniques like Driscoll–Kraay or Arellano–Bond GMM, both of which we've already implemented. This reinforces the empirical rigor of our methodology by ensuring inference validity despite time-related dependencies.

Appendix Table A4. Pesaran Test for Cross-Sectional Dependence

Test Statistic	−0.049
p-value	0.9608
Average Absolute Correlation	0.646

The Pesaran CD test fails to reject the null hypothesis of cross-sectional independence ($p = 0.961$), implying that — at least in this specification — residuals across ANSPs do not exhibit statistically significant contemporaneous correlation. While the average absolute off-diagonal correlation is moderately high (0.646), it is not sufficient to reject the assumption of independence. This suggests that conventional panel estimators remain valid, though complementary models using Driscoll–Kraay or system GMM estimators, are still prudent given the sector's structural interlinkages.

Appendix Table A5. Fisher-Type Panel Unit Root Tests (ADF) for Stationarity

Variable	Test Statistic (Pm)	p-value	Stationarity Conclusion
ln_revenue	−5.9161	1.0000	Non-stationary
capex	−5.9161	1.0000	Non-stationary
opex	−5.9161	1.0000	Non-stationary
tot_liab	−5.9161	1.0000	Non-stationary

The Fisher-type ADF tests fail to reject the null hypothesis that all panels contain unit roots for all four variables. This suggests that the series are non-stationary in levels across most ANSPs during the sample period. While this outcome is not uncommon in short panels with financial indicators, it implies that statistical inferences based on level-form regressions should be cautiously interpreted.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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