



BRIEFING

Recent European aviation ticket taxes show no measurable impact on traffic


Why we cannot yet isolate the impact of recent national tax reforms on passenger demand

Briefing published: April 2026

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Scientific review: Cambridge Econometrics



Summary

Despite being a rapidly increasing contributor to greenhouse gas emissions and non-CO₂ effects, the aviation sector has historically benefited from significant tax exemptions. Our prior [analysis](#) highlighted the scale of this issue, showing that these tax exemptions cost European governments €34.2 billion in lost revenue in 2022 alone. Some governments responded with ticket taxes to begin correcting this imbalance, in particular in the Netherlands, Germany, the United Kingdom and France. These ticket taxes can be absorbed by the airline's profit margins, if they are big enough, or passed on to the ticket price. To oppose these recent ticket tax increases, the aviation industry [claims](#) that they have a negative effect on traffic levels, the economic health of airlines and economic benefits for the regions concerned. Some airline lobbies even claim they can [quantify](#) the potential loss of tourists and economic benefits only 8 months after the introduction of the tax.

A measurable effect of taxation on demand could be expected to occur in the long term and with higher taxation levels. According to economic theory, raising ticket taxes should impact air travel: making flights more expensive should dampen demand. Yet, the reality is highly heterogeneous and, as [we highlighted previously](#), ticket prices are far from the only factor that influence traffic levels. Indeed, as [economists have emphasised](#), a number of other factors shape air travel demand, including economic conditions, the maturity of the air transport market, airline commercial strategies and aircraft manufacturers deliveries, geopolitical developments, geographic characteristics, societal shifts or even exceptional events. While statistically significant relationships between traffic levels, GDP and ticket prices can be found at a global level over a 30-year period, such broad elasticity estimates cannot reliably predict responses in individual countries in the short-term. Hence, it does not seem credible to directly link a dampening of traffic with the introduction or a small increase of a national ticket tax after a few months.

In order to bring more clarity to the debate, T&E has attempted to isolate the effect of such recent ticket taxes on traffic levels. We applied an advanced econometric method, called “difference-in-differences” to the recent tax increases in the European countries mentioned above. The study was reviewed by Cambridge Econometrics.

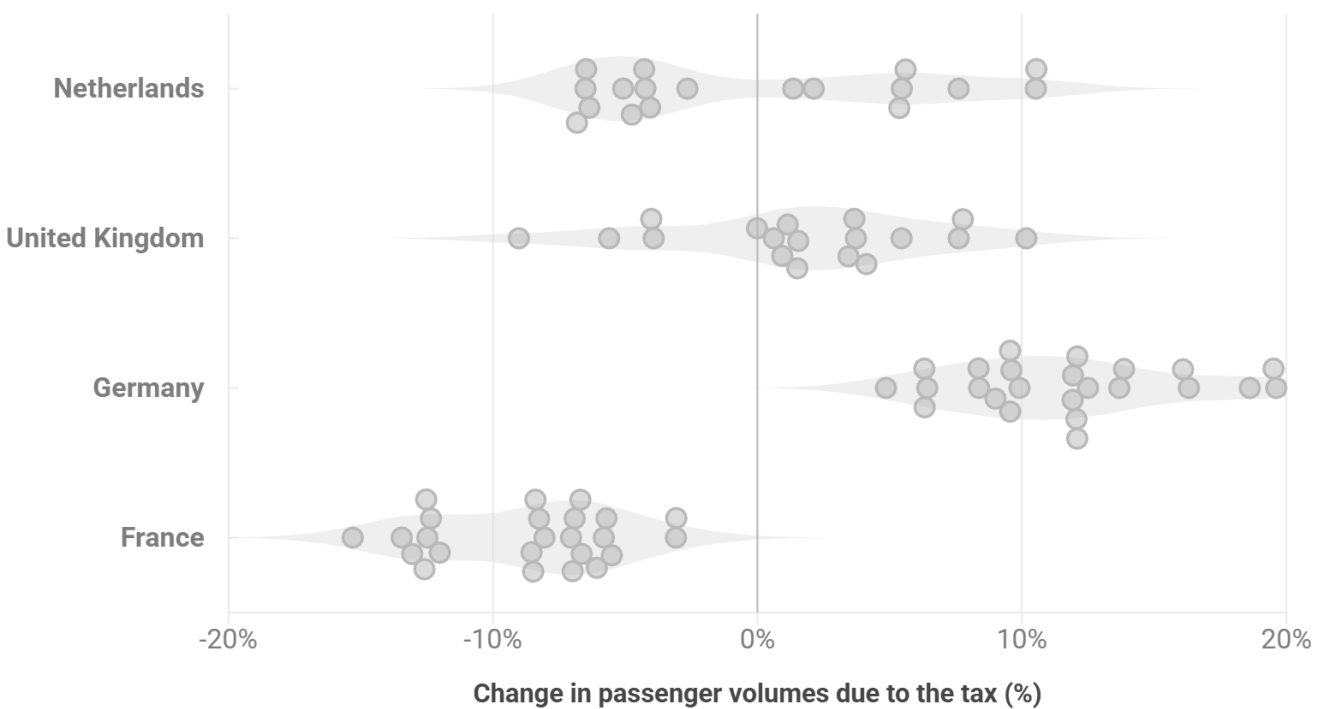
Our analysis found no statistical evidence that recent ticket taxes reduced passenger traffic across the four European case studies. The results lead us to believe that the effect of moderate tax changes are extremely difficult to detect in aggregate passenger data during a volatile post-pandemic recovery period. Across all four countries, estimates cluster around zero or show counterintuitive patterns. The tax changes certainly didn't substantially affect aviation demand, as often claimed. Several factors explain why we detect no statistical evidence that ticket taxes reduced passenger traffic. Tax size and visibility matter, but even the largest absolute increase in our study (the Dutch €18 increase to all tickets) failed to produce a statistically

detectable impact. In France and Germany, tax increases were relatively small (a few euros per ticket, rising to a few tens on long-haul flights). Airline business decisions and market context also shape outcomes. Besides, we must put these findings in context of the methodological constraints of exceptional circumstances: the unprecedented disruption of the COVID pandemic and the subsequent travel rebound. National aviation markets recovered at different speeds for reasons unrelated to taxation. To account for these differences and isolate the ticket tax impact, we employed different [statistical methods](#). However, no statistical model can perfectly isolate every influence. Whether this reflects genuinely negligible behavioural responses or simply the difficulty of measuring small effects amid market turbulence remains an open question, but for practical policy purposes the conclusion is the same: recent European ticket taxes have not measurably curbed air travel demand.

Economic analysis finds no clear evidence that ticket taxes reduced passenger traffic

Each dot represents a model configuration. Statistical significance indicates confidence that the result is not due to random chance

Statistical power ● Not statistically significant ● Statistically significant at 10%
 ● Statistically significant at 5% ● Statistically significant at 1%



Source: T&E analysis based on OAG, OECD and Eurostat • Differences-in-Differences strategy with airport and time fixed effects. Holm-Bonferroni sequential correction method. Extended control group, and 200-km radius proximity exclusions



Key findings

- 01 **Moderate tax changes are extremely difficult to detect in aggregate passenger data during a volatile post-pandemic recovery period.**
- 02 **Across all four countries analysed, estimates of ticket taxes' impacts cluster around zero or show counterintuitive patterns.**
- 03 **We didn't find any statistically significant results showing that recent tax changes substantially affect aviation demand in the four countries analysed.**
- 04 **Even the largest increase in our study (the €18 increase to Dutch tickets) failed to produce a statistically detectable impact.**
- 05 **We believe that recent European ticket taxes have not significantly curbed air travel demand.**

National ticket taxes are the most appropriate tool today for Member States to quickly fill the significant tax gap from which the aviation sector still benefits. Industry tries to keep the myth alive that such taxes could cause a collapse of traffic, but in the four countries analysed, the model we used didn't find such evidence. If increased, ticket taxes should, at best, help slow down the strong growth of traffic planned by the sector. Such growth is [not compatible](#) with the decarbonization of aviation. So ticket taxes play an essential role to both generate necessary revenues to fund clean technologies and make traffic levels compatible with net zero objectives.

T&E recommends governments to pursue ticket tax increases in order to fill the tax gap. On average across Europe, this [translates](#) into a ticket tax of €23 for a domestic journey, €51 for an intra-European journey, €259 for an extra-European journey.

01

Context

1.1 Policy context

A largely untaxed sector

Aviation is a fast-growing source of greenhouse gas emissions and non-CO₂ effects, but historically, flights have been largely untaxed. In our [2023 study](#), we showed that European tax and emission pricing exemptions amounted to €34.2 billion in 2022. This 'tax gap' is composed of €6.0 billion in exemptions from the ETS, €14.5 billion from fuel tax exemptions, and €18.8 billion in exemptions from VAT.

Policymakers are turning to ticket taxes (air passenger duties or departure levies) as a "polluter pays" tool to correct this imbalance and generate revenues to fund the transition towards a more sustainable economy. In our 2023 report, we calculated that ticket taxes generated €5.0 billion in revenues in 2022, which we subtracted from the above-mentioned exemptions to find the net tax gap of €34.2 billion. By adding a ticket tax to flight tickets, governments aim to ensure greater tax fairness compared to other sectors, implement the polluter-pays principle, and thereby generate revenues to fund policies, and in particular decarbonisation measures.

For small tax increases, airlines can decide to absorb them in their margin. For larger increases, if they can't or don't want to absorb them, they report the surcharge on the ticket price. This then raises the question whether the impact on the ticket price will have a direct effect on traffic levels, the economic health of airlines, and the economic impact of the regions concerned. This study explores this relationship further.

Recent ticket tax increases in Northern European countries

Multiple European nations recently either implemented or raised flight ticket taxes, in a context of budget constraints and high post-Covid traffic growth.

Overview of recent flight ticket tax hikes in four EU countries

	Netherlands	United Kingdom	Germany	France
Economy class				
Domestic flights	€26.43 (€7.45 → €26.43)	£6.50 (£13 → £6.50)	€15.53 (€12.73 → €15.53)	€7.40 (€2.63 → €7.40)
Intra-EEA flights	€26.43 (€7.45 → €26.43)	£13 (£13 → £13)	€15.53 (€12.73 → €15.53)	€7.40 (€2.63 → €7.40)
Extra-EEA, medium distance	€26.43 (€7.45 → €26.43)	£87 (£84 → £87)	€39.34 (€32.25 → €39.34)	€15 (€7.51 → €15)
Extra-EEA, long distance	€26.43 (€7.45 → €26.43)	£91 (£84 → £91)	€70.83 (€58.06 → €70.83)	€40 (€7.51 → €40)
Business class				
Domestic flights	€26.43 (€7.45 → €26.43)	£13 (£26 → £13)	€15.53 (€12.73 → €15.53)	€30 (€20.27 → €30)
Intra-EEA flights	€26.43 (€7.45 → €26.43)	£26 (£26 → £26)	€15.53 (€12.73 → €15.53)	€30 (€20.27 → €30)
Extra-EEA, medium distance	€26.43 (€7.45 → €26.43)	£191 (£185 → £191)	€39.34 (€32.25 → €39.34)	€80 (€63.07 → €80)
Extra-EEA, long distance	€26.43 (€7.45 → €26.43)	£200 (£185 → £200)	€70.83 (€58.06 → €70.83)	€120 (€63.07 → €120)

Source: T&E analysis based on historical rates • Dutch air passenger tax (1/01/2023), UK APD (01/04/2023), German Aviation Tax (01/05/2024), French Solidarity Tax (01/03/2025)



The Netherlands [introduced](#) a modest aviation ticket tax of €7.45 per departing passenger in January 2021, and then [increased](#) it to about €26.43 from 1 January 2023. This larger increase is part of a [strategy](#) to cut CO₂ emissions by shifting more trips from air to rail. The tax applies to all departing flights, regardless of destination (but excluding transfer passengers and air cargo), making Dutch plane tickets among the most taxed in Europe, even though it remains a fairly low level of taxation compared to the tax gap. The ticket tax was later [raised](#) to €29.05 in 2024, €29.40 in 2025 and €30.25 in 2026.

France introduced an [environmental ticket tax](#) ("eco-contribution" as a new part of the solidarity tax) in 2020, with quite low rates initially (a few euros per ticket). In March 2025, the country [increased](#) its flight taxes (e.g. economy intra-EU from ~€2.63 to €7.40). This measure is expected to generate [€850 million](#) in annual revenue. Business-class tickets and long-haul flights saw higher surcharges (for example, business intra-EU up from €20 to €30). Even after these hikes, France's passenger taxes remained fairly low compared to countries like the UK or the Netherlands.

Nordic and northern European countries have long had more structured taxation systems for air travel. A case in point is Germany, which has charged an air ticket tax since 2011 and [raised](#) the rates in 2020 as part of its Climate Action Programme. The short-haul tax was increased from €7 to about €13, with another inflation adjustment in 2024 bringing German departure taxes to roughly €15-71 depending on distance. The rationale was to align air travel costs with [climate objectives](#), but the magnitude of the change is considered to be moderate. In the last budget, Germany decided to [cancel this rise](#) and to revert to 2024 levels from 2026 onwards.

In the UK, the [Air Passenger Duty](#) (APD) remains [one of the highest](#) aviation taxes globally. The UK has levied a duty on flights since the 1990s. A notable APD reform [took effect](#) in April 2023: the government halved the APD rate on domestic flights and simultaneously created a new higher band for ultra-long-haul flights. The standard short-haul APD (~£13) for international flights remained unchanged. In essence, this policy reduced tax on UK domestic trips but slightly increased tax for long-distance travellers.

This study analyses the impact of introduction or rise of ticket taxes in four European countries. As we detail on [our taxation overview](#), other European countries have ticket taxes: Norway (between €5 and €30), Belgium (between, €5 and €10), Denmark (between €4 and €40), Austria (between €12.55 and €30), Italy (between €6.5 and €10) and Portugal (€2).

Recent tax changes provide data for assessing tax impact on traffic level

We see growing momentum across Europe to increase ticket taxes, contributing to align with the 'polluter pays' principle. This is a vital step toward closing the aviation tax gap and ensuring the industry pays its fair share. Applying the 'polluter pays' principle should theoretically encourage people to moderate their use of air transport. But it remains unclear if an increase in ticket taxes leads to a measurable drop in departing passengers. The patchwork of recent tax changes provides historical data to answer such a question.

1.2 Do ticket taxes curb demand? Evidence from the literature

A central question is whether raising ticket taxes actually reduces air travel. Economic theory suggests it should: making flights more expensive will dampen demand, especially among price-sensitive passengers, which in turn could cut flight volumes and emissions. However, ticket prices are far from the only factor that influences traffic levels as economists have [repeatedly emphasised](#):

- Economic conditions such as GDP growth, wealth distribution, and the cost of hotels and holiday activities all play a role.
- Airlines commercial strategies matter too: marketing campaigns, route selection, loyalty programs, and dynamic pricing affect where and how people fly.
- Geopolitical developments can encourage or discourage travel to certain destinations, and conflicts can close airspace entirely.

- Geographic characteristics also influence demand: some countries are large or fragmented with islands where flying is essential, while others can more easily develop rail or road alternatives. Countries with particular tourist attractions (nature, cultural heritage, entertainment facilities) naturally draw more visitors.
- Societal shifts have reshaped the market as well: business travel declined with the rise of videoconferencing during Covid, while the growth of low-cost and ultra-low-cost carriers opened new travel behaviours.
- Exceptional events such as pandemics or terrorist attacks can cause dramatic disruptions.

Moreover, the impact of ticket price changes on the willingness to travel also varies considerably by context. Business passengers whose tickets are paid by their employers are less price-sensitive than leisure travelers for whom cost can be a decisive factor in planning holidays. Moreover, the evolution of price has a stronger effect on short-haul flights where substitutes like rail exist, compared to long-haul routes where flying may be the only practical option.

We therefore see that calculating the price elasticity of air travel, meaning the relative change in demand caused by a relative variation in price, is complex, particularly over short time periods or for specific regions. While the ICAO found a [statistically significant relationship](#) between traffic levels, GDP and ticket prices at global level over a 30-year period, such broad elasticity estimates cannot reliably predict short-term responses in individual countries. Each geographic zone has its own price elasticity shaped by some of the factors mentioned above.

On top of that, structural changes in the air transport market such as the rise of videoconferencing and growth of low-cost airlines, further complicate efforts to apply historical elasticities to current conditions.

Above all, as [we showed recently](#), air connectivity is now so high in some European regions (around London, Paris, Madrid, etc.) that the impact on GDP appears to no longer be linear, as it was considered to be until now. The point where additional air travel capacity no longer facilitates economic growth appears to be reached in much of Europe (most European capitals, Southern and Western Germany, Southeast of the UK, much of Belgium, the Netherlands, Sweden, Czechia, Scandinavia).

Despite these caveats, we wanted to investigate whether rigorous econometric methods could shine light on the impact of recent ticket tax increases on traffic levels in order to acquire a critical eye on industry claims.

Empirical studies of earlier, larger aviation tax increases in stable pre-pandemic markets have found measurable demand effects. A well-known [study](#) examining Germany's and Austria's 2011 ticket taxes found passenger volumes fell by approximately 9% in the first year compared to baseline growth (and around 5% in the second year), with effects concentrated on price-sensitive leisure routes while major hub airports saw little change.

A more recent [analysis](#) found a 6 to 11% reduction in passengers departing annually from Germany in the first two years after the 2011 tax implementation. [Research](#) on Sweden's 2018 aviation tax observed comparable impacts.

However, these studies examined substantially higher tax levels in fundamentally different market conditions. This allowed clearer baseline identification and effect detection. Overall, the literature research indicates that ticket taxes do have a dampening effect on air travel demand, roughly on the order of a high-single-digit percentage drop in passengers. However, the impact depends on the tax magnitude, design and context.

This analysis addresses a distinct policy question: can modest, recent reforms produce measurable short-term impacts under current market conditions?

Our study explores whether similar effects are detectable for the moderate tax adjustments implemented across Europe since 2023. Reforms occurring during exceptional post-pandemic market volatility. We tested whether post-COVID tax reforms produced measurable impacts in an environment characterised by double-digit year-over-year traffic swings driven by pandemic recovery dynamics. Using a difference-in-difference statistical approach and focusing on the most recent European tax increases, our study was unable to find any impact of the ticket tax increases.

Impact of ticket taxes: evidence from four country case studies

2.1 The difference-in-difference approach

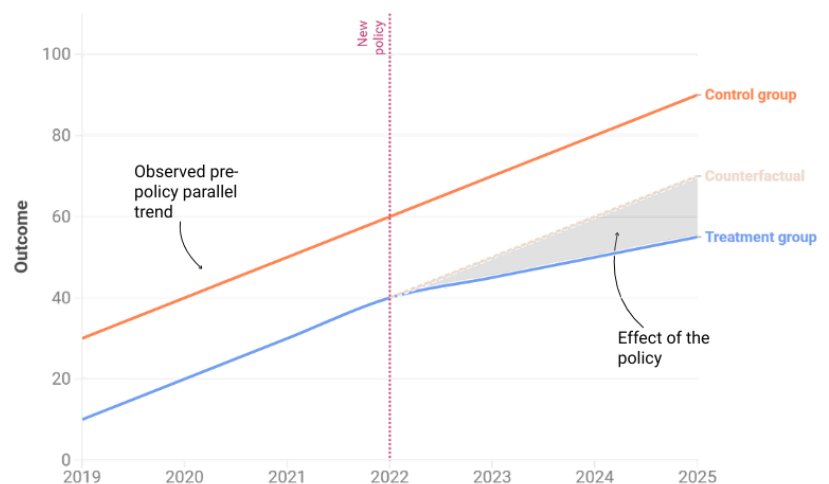
We estimated the potential impact of recent ticket tax changes in four countries using a [difference-in-differences \(DiD\) design](#), a quasi-experimental technique used to estimate causal effects. This method works by comparing changes in outcome (air travel trends) over time between the countries that raised their tax (the "treated" countries) against what we estimate would have happened without the tax (the "control" countries). This [method](#) is typically used to [assess](#) the impact of a policy, when it is not possible to run any experiment in a laboratory.

To isolate the impact of ticket taxes, we created a control group using a similar set of countries that did not change their tax systems. Our core control group consists of Spain, Italy, Ireland, Poland, Portugal, Czechia, Switzerland and Denmark.¹ These countries are meant to represent the natural evolution of air travel during this period, without a ticket tax increase.

We apply this "lack of taxation" scenario from the control group to the treated countries to create a counterfactual, essentially building a "fake" version of the treated country as if a tax hadn't been levied. The difference between the actual traffic and this counterfactual is expected to reflect the tax effect.

In doing so, we try to isolate the impact of the tax itself. In essence, the method asks: *"did passenger traffic in the taxed country grow differently than it would have, based on trends in comparable countries?"*. In this regard, the control group serves only to help us construct how the treated country's passenger numbers would have evolved without the tax change.

Illustration of the Difference-in-differences (DiD) method



Source: T&E (2026)



¹ Italy and Portugal have ticket taxes, but those are very small and have been introduced well before the period analysed. Denmark introduced its own air passenger tax in January 2025, making it suitable as a control for earlier periods (pre-2025), but not afterwards (post-2025).

Clearly, the tax is not the only element that has changed between the two groups of countries (treatment and control). For this reason, other factors that could distort the results are controlled for. In econometrics, these are called covariates. We account for each airport's baseline size, so that we are not simply comparing large airports with small ones, and we also take into account normal seasonal patterns, such as summer travel peaks and winter drops.

Economic variables such as GDP per capita, unemployment, inflation, fuel prices and tourism are also added to the model. This is important because if passenger growth slows, it is important to know whether this is due to the tax, the economic downturn, the increase in fuel prices, or other factors. By controlling such parameters, the effect of the tax alone can better be isolated.

The strength of this type of design is its ability to mimic a “natural experiment”. By controlling for confounding factors, any persisting difference can be attributed to the policy change, under the assumption that, with no tax, the treated and control groups would have followed similar paths. We tested this assumption by trying different control groups and time windows, ensuring that our conclusions do not hinge on one particular model or comparison.

We also used robust statistical inference to ensure that any measured effects are genuine rather than statistical artifacts. Specifically, standard errors at the airport level were clustered to account for correlation within airports over time. In addition, we used a conservative statistical procedures to ensure the reliability and accuracy of our results, which are not sensitive to the specific features of our sample. If a result appears significant in our main analysis but loses significance under these more conservative testings, we interpret it cautiously as directional evidence rather than definitive proof.

Each of these assumption sets lead to a regression result, displayed as a dot in the graph below. Nonetheless, applying such a method on the European air market goes not without limits. Even by taking into account control variables, some factors specific to the countries can't be included in the modelling. Results have to be taken with a critical eye. In addition, due to the specificity of each country, the results can only be applied to those countries and cannot be extrapolated to other contexts.

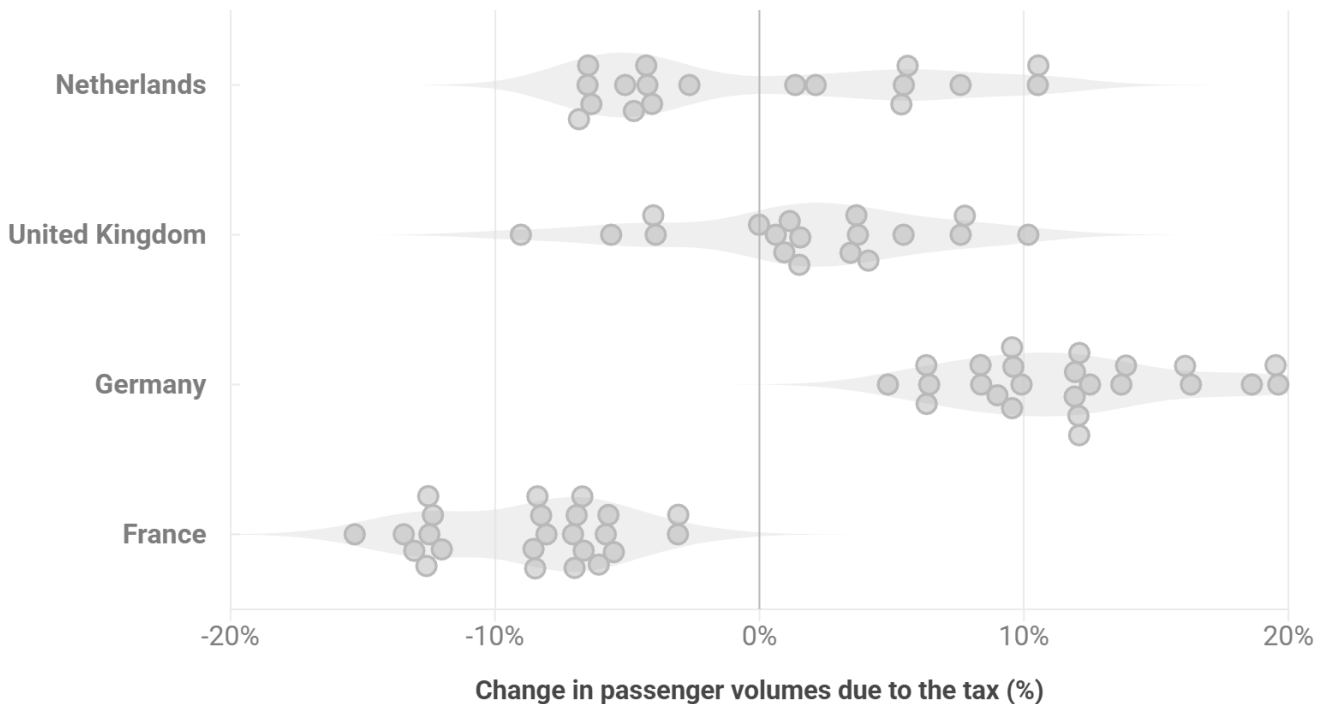
2.2 Cross-country findings

Our analysis found no statistical evidence that recent ticket taxes reduced passenger traffic across the four case studies. The applied method was unable to measure the effects amid the volatile post-pandemic recovery. However, the data trends suggest that where these taxes do have an impact, they translate into a slight slowing of passenger growth. The results lead us to believe that while moderate tax changes are extremely difficult to detect in aggregate data during a volatile post-pandemic recovery period, they apparently do not cause dramatic traffic reductions, as suggested by certain industry actors.

Economic analysis finds no clear evidence that ticket taxes reduced passenger traffic

Each dot represents a model configuration. Statistical significance indicates confidence that the result is not due to random chance

Statistical power ● Not statistically significant ● Statistically significant at 10%
● Statistically significant at 5% ● Statistically significant at 1%



Source: T&E analysis based on OAG, OECD and Eurostat • Differences-in-Differences strategy with airport and time fixed effects. Holm-Bonferroni sequential correction method. Extended control group, and 200-km radius proximity exclusions



To understand these results, we look at two key metrics: the estimated percentage change and its statistical significance. When our model shows a negative estimate, such as a 5% reduction, it means passenger volumes were five percent lower than our expected baseline trend without the tax. However, we also need to know if this drop is a genuine reaction to the policy or just random market noise. That is why statistical significance is key. A result with a 10% significance level means we are 90% confident that the tax caused the change. If a result is not statistically significant, the signal is too weak to separate from normal traffic fluctuations.

Applying this to our case studies, the Netherlands shows passenger numbers were 5% to 7% lower than the expected baseline between 2022 and 2025. Yet, because none of these results reach statistical significance, we cannot reliably attribute this slowdown to the tax.

In the United Kingdom, the estimates hover near zero, ranging from slight positive to slight negative effects, showing no meaningful impact and no statistical significance.

France shows estimates of 6% to 9% fewer passengers compared to the baseline in some specifications but again none of the results reach statistical significance.

Finally, Germany illustrates how sensitive these models are to macroeconomic shocks. Several specifications produced positive estimates, implying passenger numbers rose after the tax increase. This contradicts economic theory and underlines the difficulty of isolating small policy effects in a sector still adjusting to unprecedented disruption.

The lack of robust findings reflects both genuine policy effects and methodological challenges, including taking into account the heterogeneous effects of COVID recovery. Results depend strongly on the time window chosen. When we use continuous windows that include the recovery years (2020-2022), estimated impacts remain small and statistically insignificant across all four countries.

The overarching pattern is clear. When we apply conservative statistical inference methods designed for settings with limited treated units, no country shows a statistically robust reduction in passenger traffic following ticket tax increases. Many estimates cluster around zero. Where larger effects appear, they either fail rigorous significance testing or emerge only in gap specifications that span the pandemic disruption. Moderate tax changes appear not to be detectable in aggregate passenger data under current market conditions, and they certainly do not crash aviation demand. Any potential dampening effect on growth remains too small to measure reliably with the method used here and falls far short of the dramatic impacts often claimed in public debates about competitiveness and job losses.

2.3 Understanding the limited impact and methodological constraints

Several factors explain why we detect no statistical evidence that ticket taxes reduced passenger traffic. Tax size and visibility matter, but even the largest increase in our study (the €18 increase to Dutch tickets) failed to produce a statistically detectable impact. In France and Germany, tax increases were relatively small (a few euros per ticket, rising to a few tens of euros on long flights) and often absorbed into the total fare. The United Kingdom's 2023 APD reform actually lowered costs for domestic trips, offsetting increases on ultra-long routes that represent only a fraction of departing traffic. These modest price signals appear insufficient to deter aggregate travel patterns measurably.

Airline business decisions and market context also shape outcomes. For example, Ryanair responded to France's tax increase by [shifting](#) aircraft capacity away from three regional airports to more profitable routes elsewhere, using the tax as public justification. While this highly publicised move caused localised traffic reductions at specific airports, it reflects airline route optimisation rather than a pure drop in passenger demand across the country. The availability of alternatives plays a role as well: Dutch travelers can substitute short flights with cross-border rail relatively easily, whereas UK passengers have fewer practical alternatives for many routes.

We must contextualise these findings within the methodological constraints of observational studies conducted during exceptional circumstances. In this particular case, timing presents the most significant challenge. All tax changes we analysed occurred during or immediately after the unprecedented disruption of the Covid-19 pandemic and the subsequent travel rebound. Detecting a minor drag from a ticket tax is extraordinarily difficult when overall traffic exhibits double-digit growth rates during recovery phases.

National aviation markets recovered at different speeds for reasons unrelated to taxation. Germany's sluggish recovery reflected its specific airline network structure and passenger mix rather than its May 2024 tax policy. Overlapping regulations add noise: France's short-haul flight ban and Amsterdam Airport Schiphol's passenger cap both affect traffic independently of ticket taxes, making it harder to isolate the tax effect specifically.

To account for these differences and isolate the ticket tax impact, we employed statistical controls and fixed effects. Controls filter out traffic changes driven by observable factors such as GDP growth, unemployment rates, fuel prices and tourism flows. Fixed effects account for permanent structural differences between countries, including, for example, geographic constraints and the existing quality of rail networks. These methods substantially improve our ability to isolate the tax effect from confounding factors.

However, no statistical model can perfectly isolate every influence. Aviation markets are extraordinarily complex, and many real-world developments (airline pricing strategies, competitive dynamics, consumer sentiment shifts) are impossible to quantify in a mathematical model. These unobservable factors leave residual noise in the data. Some minor traffic fluctuations we observe may be driven by these hidden dynamics rather than pure responses to tax policy.

Testing the parallel trends assumption proves challenging given volatile post-pandemic recovery patterns and differing market structures across European countries. While our diagnostic tests suggest the assumption generally holds, some uncertainty remains. Most critically, our statistical power is constrained because we analysed only one treated country at a time. Tax schemes and implementation timings vary significantly across Europe, making it unrealistic to pool countries into a single analysis. We therefore conduct separate case studies and apply conservative inference methods. For all these reasons, we interpret results cautiously.

With our econometric approach, modest tax adjustments show no statistically detectable effect on aggregate passenger numbers in the short term. Whether this reflects genuinely negligible behavioral responses or simply the difficulty of measuring small effects amid market turbulence remains an open question, but for practical policy purposes the conclusion is the same: **recent ticket taxes in France, Germany, the Netherlands and the UK have, according to our methodology, not measurably curbed air travel demand.**

03

Recommendations

Our analysis shows that, contrary to what industry claims, there is no evidence of the impact of recent ticket tax increases on air travel demand. Whilst we don't claim that taxation has no impact on traffic level, we stress that it remains challenging to isolate it from other factors, over such a short period of time and in a heterogeneous and dynamic context. Such conclusions help nuancing claims that predict a collapse of traffic due to taxation. They should strengthen governments in their will to fill the massive tax gap from which airlines still benefit. National ticket taxes are an appropriate tool for Member States to act quickly and efficiently. Also, they present the advantage of enabling taxation of aviation without creating risks for competitiveness of European stakeholders, for several reasons:

- Such taxes apply to the final destination of passengers, there is hence no risk of leakage.
- They are paid by all airlines, European or not, on all flights departing the national ground.
- There is no risk to deteriorate the competitiveness of European hubs as ticket taxes exempt transfer passengers.
- Besides, it is possible [to exempt outermost residents](#) from ticket taxes, for whose aviation connectivity is an issue of territorial continuity.

If significantly increased, ticket taxes should help slow down the strong growth of traffic planned by the sector. [As we showed](#), such growth is not compatible with the decarbonization of aviation. So ticket taxes play an essential role to both generate necessary revenues to fund clean technologies and make traffic levels more compatible with net zero objectives.

T&E recommends that governments pursue ticket tax increases in order to fill the aviation tax gap. [As we calculated previously](#), this translates on average across Europe into a ticket tax of €23 for a domestic journey, €51 for an intra-European journey, €259 for an extra-European journey.

Annex I: Detailed methodology

Overview and research design

The following sections detail each step of our approach.

Data sources and variable construction

Our primary data source is [OAG Traffic Analyser](#), which provides comprehensive information on passenger volumes, origin and destination airports, stopover patterns for indirect journeys and operating airlines for each flight segment. The dataset covers January 2019 through December 2025 and includes all major European commercial airports.

We construct our main dependent variable as the natural logarithm of monthly departing passengers at each airport. The logarithmic transformation serves two purposes. First, it normalises the highly skewed distribution of passenger counts, where a few major hubs handle millions of passengers while many regional airports handle far fewer. Second, it allows us to interpret our regression coefficients as approximate percentage changes, which is the standard approach for measuring policy impacts and elasticities.

To isolate the tax effect from broader economic drivers of air travel demand, we control for time-varying macroeconomic variables matched to each airport based on its country and observation month. These controls are essential to avoid omitted variable bias, where a decline in traffic caused by economic factors could be mistakenly attributed to the tax. The table below summarises our key variables and data sources.

Variable category	Metric	Source	Frequency	Note
Traffic	Departing passengers	OAG	Monthly	Primary measure of demand
Flights	Flight counts & schedules	OAG	Monthly	Primary measure of emissions
Economic output	GDP per capita at current prices (calendar and seasonally adjusted, PPP converted)	OECD	Quarterly	Proxy for economic growth; entered in logarithmic form
Labour market	Unemployment rate (calendar and seasonally adjusted)	OECD	Monthly	Proxy for consumer confidence

Inflation	CPI/HICP index for fuels and lubricants for personal transport equipment (CP0722) (growth rate, period on period)	OECD	Monthly	Controls for cost-of-living effects on spending.
Energy costs	CPI/HICP index for (growth rate, period on period)	OECD	Monthly	Controls for airline cost-push inflation
Tourism	Foreign tourist visits/arrivals at tourist accommodation establishments	Eurostat , ONS	Monthly	Controls for tourism flows, entered in logarithmic form

Overview of main variables used in T&E's analysis

We enter both GDP per capita and foreign tourist arrivals in logarithmic form, allowing their coefficients to be interpreted as elasticities. Inflation and unemployment rates are entered as percentages, following standard conventions in macroeconomic modelling.

We processed these diverse data sources into a single unified panel dataset where each observation represents one airport in one month. This required addressing several data challenges. Given the short time windows under study, we focused on maximising data availability. To this end, we worked with monthly data and converted all non-monthly data to this periodicity. This is the case of quarterly variables such as GDP per capita and UK foreign tourist arrivals. We distributed the quarterly total evenly across the three constituent months.

Our analysis extends through December 2025, for which official statistics are available for most variables. However, some series remain incomplete for historical data. For isolated missing monthly data in otherwise complete series, we calculated the value based on the annual total from the same source.

If both the monthly observation and annual total were unavailable, we used forward imputation by applying a constant year-over-year growth multiplier. We calculate this multiplier for each country as the ratio of the most recent available monthly observation to the corresponding month in the previous year. To forecast a missing future month, we multiply the value from exactly 12 months earlier by this growth multiplier. This approach assumes that the growth trend observed in the most recent available data persists through the missing period.

We also performed targeted imputations to fill in historical yearly gaps. Where monthly observations are missing for a specific country and year, we reconstructed them using patterns from adjacent years or growth rates. A case in point is tourist arrivals in Ireland for 2019. We

applied the 2018 seasonal pattern to distribute the known annual total across the months, under the assumption that tourism seasonality remains relatively stable year over year.

Sample construction and exclusion criteria

Our baseline sample includes all commercial airports in both treated countries (those introducing or raising taxes) and control countries (those maintaining stable tax regimes over the same period). However, including every airport indiscriminately would produce invalid comparisons. We therefore apply strict exclusion criteria to ensure that the control group provides a valid counterfactual.

The most significant threat to validity in difference-in-differences studies is spillover effects. If a country introduces a tax, people residing in close proximity to international borders might drive to airports in neighboring countries to avoid paying the higher fare. If that neighboring country is in our control group, we would observe two effects simultaneously: the treated airport loses passengers (the demand effect we want to measure) and the control airport gains passengers (a spillover we want to exclude). This double-counting would exaggerate the apparent tax impact.

To address this, we applied a proximity exclusion rule, removing any control airport located within 200 kilometers of an airport in the treated country. For example, when analysing France, we excluded nearby control airports in Italy, Spain and Switzerland that passengers might easily access as substitutes. This ensures our estimated effect captures genuine changes in demand.

However, we make pragmatic exemptions to this rule for certain airports where spillover effects are implausible despite geographic proximity. The rule is not applied to the United Kingdom, due to its unique geography. Similarly, we retained island airports (such as Sardinian airports) and smaller regional facilities in the sample, as cross-border tax avoidance opportunities would require disproportionate effort.

We also retain major hub airports and regional airports with limited cross-border accessibility even when they fall within the 200-kilometer threshold. For instance, we keep Prague (PRG) and Copenhagen (CPH) in the German case' control group despite their proximity to the German borders, because these are substantial airports serving distinct catchment areas with limited realistic spillover potential to nearby foreign airports.

The full list of exceptions to the proximity exclusion rule is provided below. These exemptions aim to prevent unnecessary sample restrictions, while maintaining the integrity of our identification strategy.

Country	Airport name	Airport code	Airport name	Airport code
Italy	Alghero-Fertilia Airport	AHO	Milan Malpensa Airport	MLP
	Marina di Campo Airport	EBA	Olbia Costa Smeralda Airport	OLB
	Florence Airport	FLR	Pisa International Airport	PSA
	Oristano-Fenosu Airport	FNU	Siena-Ampugnano Airport	SAY
	Grosseto Airport	GRS	Tortoli Airport	TTB
	Lucca-Tassignano Airport	LCV		
Poland	Poznań-Ławica Airport	POZ		
Czechia	Václav Havel Airport Prague	PRG		
Denmark	Aarhus Airport	AAR	Hans Christian Andersen Airport (Odense)	ODE
	Billund Airport	BLL	Roskilde Airport	RKE
	Copenhagen Airport	CPH	Bornholm Airport	RNN
	Esbjerg Airport	EBJ	Sønderborg Airport	SQW
	Midtjyllands Airport (Karup)	KRP	Stauning Vestjylland Airport	STA
Switzerland	St. Gallen-Altenrhein Airport	ACH	Sion Airport	SIR
	Ascona Airport	ACO	Grenchen Airport	ZHI
	Bern Airport	BRN	Interlaken Airport	ZIN

	Buochs Airport	BXO	Locarno Airport	ZJI
	Emmen Air Base	EML	Zurich Airport	ZRH
	Lugano Airport	LUG		

Overview of the neighbouring airports included in the analysis

We also prioritised maintaining a balanced panel for our core specifications. An airport remains in our sample only if it has valid data for the essential covariates throughout the analysis period. Although, as mentioned above, we tried to maximise data coverage for all variables of interest, with the exception of passengers and departures, we dropped any airport-month observation that lacks critical data and cannot be reliably imputed. This prevents our results from being driven by changes in sample composition (such as airports dropping in and out of the dataset) rather than genuine changes in passenger behavior.

Treatment definition and control group selection

We defined treatment as the implementation or increase of an aviation tax. We created a treatment indicator that equals one for all airports in a country undergoing a tax change and zero for airports in control countries. We also created a post-treatment indicator that equals one for all months on or after the tax implementation date. The primary variable of interest in our regression is the interaction between these two indicators, which captures the differential change in passengers for treated airports during the post-treatment period.

Selecting an appropriate control group is critical for valid causal inference. Our core control group consists of Spain, Italy, Ireland, Poland, Portugal, the Czech Republic, Switzerland and Denmark. We selected these countries because they represent European aviation markets of comparable structure and scale but experienced no significant aviation tax changes during our study windows. In essence, we treat their collective trend as representing a stable European baseline against which to measure tax effects.

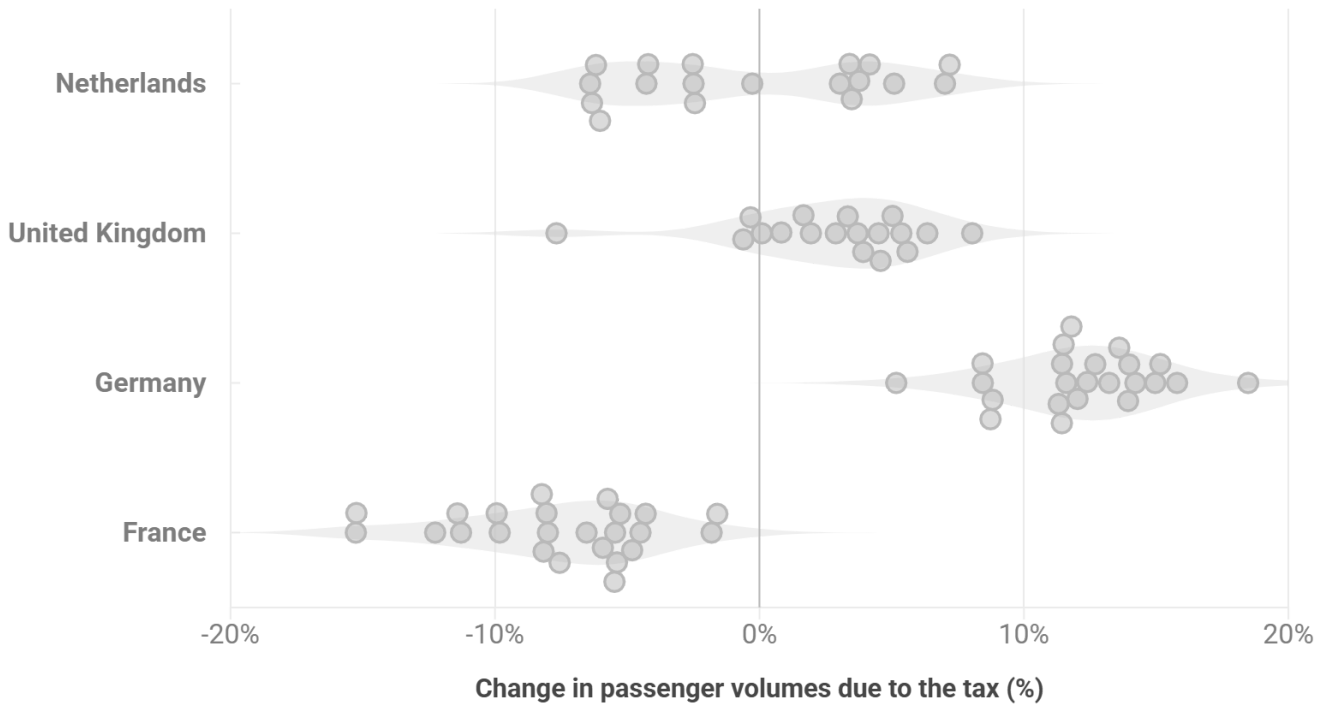
Denmark and Switzerland warrant special mention. Denmark introduced its own air passenger tax in January 2025. This makes it suitable as a control for earlier periods (pre-2025 years) but not for 2025 itself. Switzerland offers a useful comparison as a non-European Union member with different economic dynamics. The inclusion of these countries in our extended control group helps verify that our findings are not driven by the idiosyncratic performance of any single control country.


For robustness testing, we also estimated the specifications using narrower control groups; a smaller control group, with Switzerland and Denmark removed; and an alternative control group of Italy, Ireland, Poland, the Czech Republic and Switzerland (with Spain and Portugal removed).

Economic analysis finds no clear evidence that ticket taxes reduced passenger traffic

Each dot represents one model configuration. Statistical significance indicates confidence that the result is not due to random chance

Statistical power ● Not statistically significant ● Statistically significant at 10%
● Statistically significant at 5% ● Statistically significant at 1%



Source: T&E analysis based on OAG, OECD and Eurostat • Differences-in-Differences strategy with airport and time fixed effects. Holm-Bonferroni sequential correction method. Alternative, reduced control group, and 200-km radius proximity exclusions 

The aim was to verify that our results do not depend on the specific composition of the control group. These sensitivity tests help confirm that our findings reflect genuine patterns rather than artifacts of control group selection. If the estimated tax effect remains stable across all iterations, we gain confidence that no single control country is driving the result.

Economic analysis finds no clear evidence that ticket taxes reduced passenger traffic

Each dot represents one model configuration. Statistical significance indicates confidence that the result is not due to random chance

Statistical power ● Not statistically significant ● Statistically significant at 10%
 ● Statistically significant at 5% ● Statistically significant at 1%



Source: T&E analysis based on OAG, OECD and Eurostat • Differences-in-Differences strategy with airport and time fixed effects. Holm-Bonferroni sequential correction method. Reduced control group, and 200-km radius proximity exclusions



Econometric specification

Our core analytical tool is a two-way fixed effects difference-in-differences regression model estimated using ordinary least squares. The baseline regression equation estimated takes the form:

$$\ln(P_{it}) = \alpha_i + \gamma_t + \beta(Treat_i * Post_t) + \delta X_{ct} + \epsilon_{it}$$

Put simply, the components of this equation work together to isolate the tax effect. The dependent variable $\ln(P_{it})$ is the natural logarithm of departing passengers at airport i in year-month t . The airport fixed effects (α_i) absorb all time-invariant characteristics of each airport, such as its size, runway capacity, distance to the nearest city center and business model (whether it operates as a hub or serves primarily regional traffic). The date fixed effects (γ_t)

absorb common shocks affecting all airports simultaneously in any given month, including the seasonality of European travel, global oil price movements and continent-wide economic conditions.

The coefficient of interest (β) measures the average treatment effect on the observation. It captures only the variation in passenger traffic that correlates with the tax introduction after removing both airport-specific baseline levels and common time trends. The vector X_{ct} includes our time-varying control variables (GDP per capita, unemployment, inflation, fuel prices and tourism) for country c in year-month t . The error term ϵ_{it} captures remaining unexplained variation.

Given our log-linear specification, the coefficient β represents a semi-elasticity. For small values (less than 0.10 in absolute terms), we can interpret β directly as an approximate percentage change. For example, a coefficient of -0.05 implies roughly a 5% reduction. For larger coefficients - or as a general rule - we can apply the following transformation to obtain the precise percentage change:

$$\% \Delta = (e^{\beta} - 1) * 100$$

We prioritise results that are stable in sign across different specifications and statistically significant under conservative inference methods. This triangulation of evidence helps ensure our findings reflect real-world behavioral responses rather than statistical artifacts.

We interpret our results primarily as directional indicators and order-of-magnitude estimates rather than precise point estimates. Given the inherent complexities of the post-pandemic aviation market, the short timeframe to observe effects (especially for Germany and France) and various confounding factors at play, we focus on understanding whether taxes had a measurable impact and approximately how large that impact was, rather than claiming to pin down exact percentage effects. This approach acknowledges the uncertainty inherent in quasi-experimental methods while still providing meaningful guidance on the likely scale and direction of tax impacts.

To test the robustness of our findings and understand how different control variables influence the results, we estimated six distinct model specifications. Model M0 includes only the tax effect and fixed effects, providing a baseline. Models M1 through M4 progressively add different combinations of economic controls: M1 adds logarithm of GDP per capita and inflation; M2 replaces GDP with unemployment; M3 combines logarithm of GDP with fuel prices; M4 includes unemployment, inflation and logarithm of foreign tourist arrivals. Model M5 is our most comprehensive specification, including logarithm of GDP per capita, inflation, fuel prices and

logarithm of foreign tourist arrivals simultaneously. This step-up approach aims to reveal how sensitive our estimated tax effect is to the inclusion of various economic controls.

Model name	Model equation
Only fixed effects (M0)	$\ln(P) \sim Tax\ Effect + Airport\ FE + Date\ FE$
Macroeconomic trends (M1)	$\ln(P) \sim Tax\ Effect + \ln(GDP\ per\ capita) + inflation + Airport\ FE + Date\ FE$
Labour trends (M2)	$\ln(P) \sim Tax\ Effect + unemployment + inflation + Airport\ FE + Date\ FE$
Energy trends (M3)	$\ln(P) \sim Tax\ Effect + \ln(GDP\ per\ capita) + fuel\ prices + Airport\ FE + Date\ FE$
Tourism trends (M4)	$\ln(P) \sim Tax\ Effect + unemployment + inflation + \ln(foreign\ tourists\ arrivals) + FEs$
Full equation (M5)	$\ln(P) \sim Tax\ Effect + \ln(GDP\ per\ capita) + inflation + \ln(foreign\ tourists\ arrivals) + fuel\ prices + FEs$

Overview of model specifications used in the T&E analysis

Statistical inference and significance testing

Proper estimation of standard errors is crucial to avoid false positive findings (Type I errors). Our data structure creates correlation challenges: residuals are likely correlated within the same airport over time (serial correlation) and potentially across airports within the same country (spatial correlation). Conventional standard errors would treat each airport-month observation as independent, leading to artificially narrow confidence intervals and overstated statistical significance.

We address serial correlation by clustering standard errors at the airport level. This accounts for the fact that demand shocks at a single airport (such as a local labor strike or runway maintenance) persist across multiple months. Airport-level clustering produces appropriately conservative standard errors that reflect this temporal dependence.

However, a known limitation of clustered standard errors is that they can be unreliable when the number of treated clusters is [small](#). In our study, although we observe hundreds of airports, treatment is assigned at the country level. Each analysis involves only one treated country (the Netherlands, UK, Germany, or France respectively), meaning standard asymptotic assumptions underlying cluster-robust inference may fail.

To address this issue, we employ the [Wild Cluster Bootstrap method](#), specifically the variant proposed by [Cameron, Gelbach and Miller \(2008\)](#). This technique resamples the data at the country level to generate an empirical distribution of the test statistic under the null hypothesis of no treatment effect. We run 9,999 bootstrap iterations to ensure high precision in our p-values. We report both conventional cluster-robust p-values and bootstrap p-values. When a result appears significant under conventional methods but loses significance under the bootstrap, we interpret it cautiously as directional evidence rather than definitive proof of an effect.

Correcting for multiple hypothesis testing: the Holm-Bonferroni method

A critical statistical challenge in our analysis stems from multiple hypothesis testing. We estimated numerous model specifications for each country: six different control variable combinations (M0 through M5), multiple time windows and various sensitivity checks. This creates dozens of statistical tests per country. Even if aviation taxes truly had no effect, we would expect some specifications to show statistically significant results purely by chance, a phenomenon known as false discovery or Type I error inflation.

The conventional approach to statistical significance sets a threshold (typically $p < 0.10$ or $p < 0.05$) for each individual test. However, when conducting multiple related tests simultaneously, this approach becomes unreliable. If we run 30 tests at the 10% significance level, we would expect approximately three false positives even if no real effects exist. Without correction, readers might mistakenly interpret these spurious findings as evidence of genuine tax impacts.

To address this problem, we apply the Holm-Bonferroni sequential correction procedure. This method controls the family-wise error rate, that is the probability of making at least one Type I error across the entire set of tests for a given country. The procedure works as follows:

First, we gather all p-values from our specifications for a given country (for example, all Netherlands results across different models and time windows). We then rank these p-values from smallest to largest. For the smallest p-value (the most "significant" result), we compare it against the threshold α/n , where α is our target significance level (0.10 or 0.05) and n is the total number of tests. If this first p-value exceeds the threshold, we stop - none of the results are significant. If it passes, we move to the second-smallest p-value and compare it against $\alpha/(n-1)$. We continue this sequential testing, adjusting the threshold at each step as $\alpha/(n-k+1)$ where k is the test's rank.

This procedure is less conservative than the simple Bonferroni correction (which divides α by n for all tests) because it exploits the sequential structure: once we reject a hypothesis at step k , all subsequent tests face slightly less stringent thresholds. However, it still provides strong protection against false discoveries across the full set of comparisons.

Importantly, the p-values reported in our dot plot charts reflect these Holm-Bonferroni sequential corrections. A result marked as "statistically significant at 10%" has passed this rigorous multiple testing correction, meaning we can be confident it is not a statistical fluke arising from testing many specifications. Results that appear significant under conventional single-test p-values but fail the Holm-Bonferroni correction are reported as non-significant, reflecting our conservative approach to inference.

This correction substantially affects our conclusions. Several specifications that initially appeared marginally significant under conventional testing (particularly for the Netherlands and France) lose significance once we account for multiple comparisons. This reinforces our overall finding of no statistically robust evidence of a short term impact of recent aviation taxes.

Sensitivity and robustness checks

We subject our core findings to extensive sensitivity testing to verify they do not depend on arbitrary modelling choices. These tests examine whether results hold under various [model specifications](#), [alternative control groups](#) as well as different [time windows](#) and [proximity exclusion rules](#).

Parallel trends assumption

The fundamental identifying assumption of difference-in-differences models is parallel trends: in the absence of the tax, treated and control groups would have followed similar trajectories. We assess this assumption in two ways. First, we visually inspect the data by plotting average passenger counts for treated and control groups over time, looking for consistent patterns of movement prior to tax implementation. More importantly, we conducted formal statistical tests by running placebo regressions on pre-treatment data only, interacting the treatment indicator with time trends. Statistically insignificant coefficients on these interactions support the parallel trends assumption, confirming that the groups were not already diverging before the tax was applied.

Time windows

The choice of time window is particularly critical given that our study period (2019 through 2025) includes the unprecedented disruption of Covid-19. To ensure our results are not driven by volatile pandemic recovery patterns, we test multiple time window scenarios.

Time windows
2019-2025
2021-2025
2022-2025
2023-2025

Overview of time windows tested

We prioritised post-pandemic specifications¹ because Covid-19 represents a massive structural shock in aviation markets. The sector fundamentally changed during the pandemic, making pre-2020 patterns potentially less relevant for understanding current dynamics. Post-pandemic specifications provide cleaner identification by comparing relatively similar market conditions before and after tax changes.

Proximity exclusions

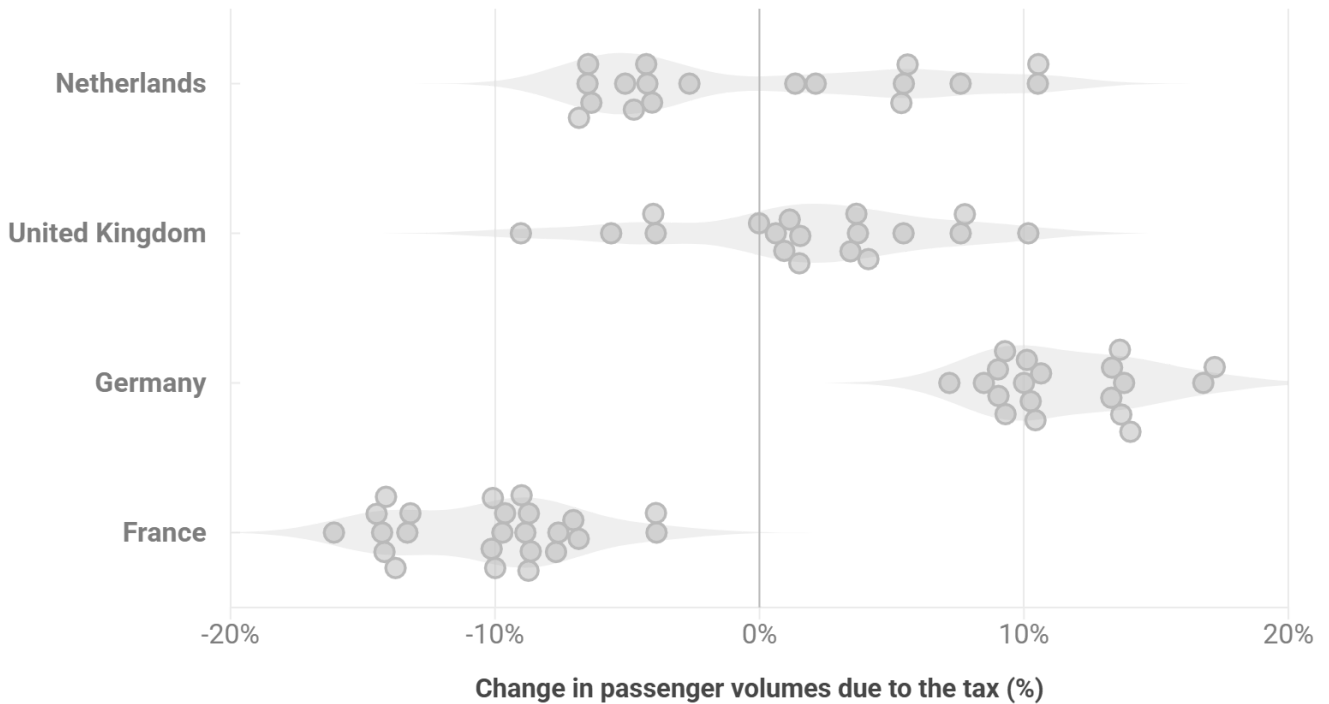
To assess whether potential cross-border traffic shifts affect our conclusions, we verified the robustness of our findings by testing different border exclusion zones, such as a broader 350 km radius and the opposite extreme, no exclusions whatsoever. Meaning all departing passengers from the country.

¹ For the Netherlands and United Kingdom, where tax systems changed in 2023, we used only pre-2023 time windows.

Economic analysis finds no clear evidence that ticket taxes reduced passenger traffic

Each dot represents one model configuration. Statistical significance indicates confidence that the result is not due to random chance

Statistical power ● Not statistically significant ● Statistically significant at 10%
● Statistically significant at 5% ● Statistically significant at 1%



Source: T&E analysis based on OAG, OECD and Eurostat • Differences-in-Differences strategy with airport and time fixed effects. Holm-Bonferroni sequential correction method. Extended control group, and 350-km radius proximity exclusions

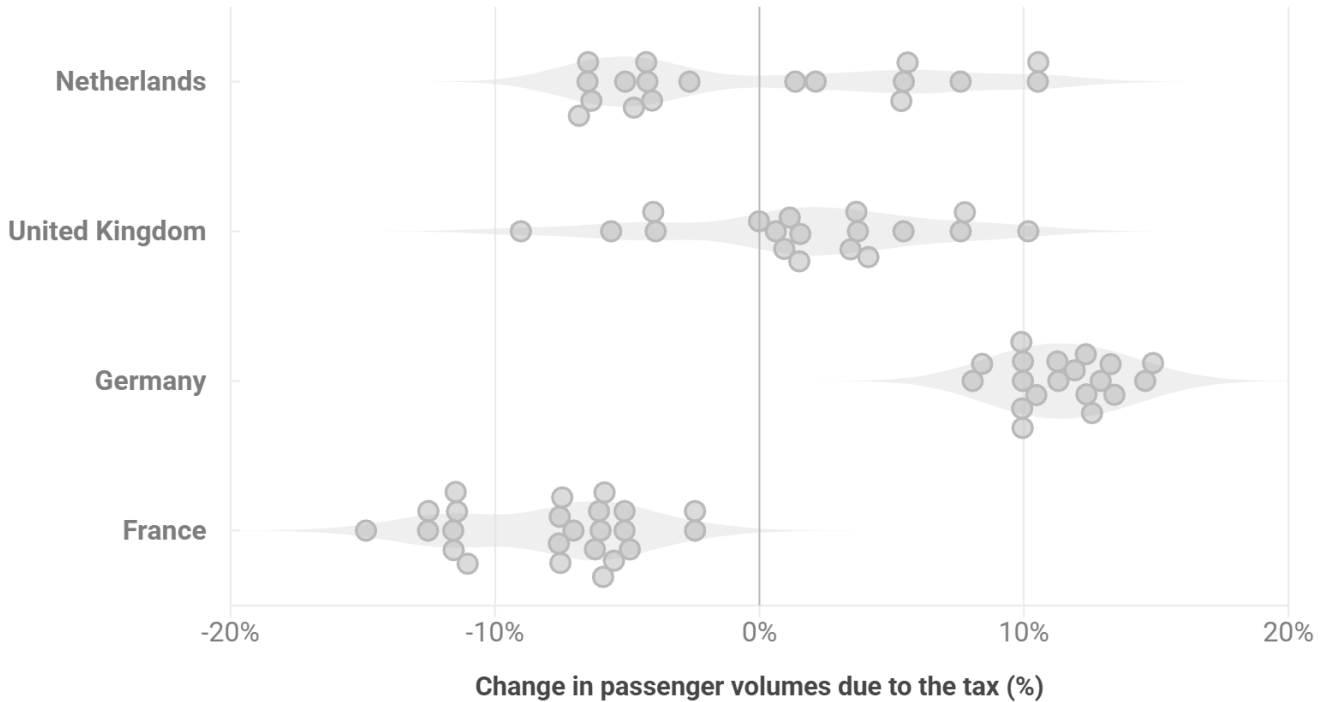


These extensive robustness checks allow us to assess the stability and reliability of our findings across different modelling assumptions, providing a comprehensive picture of how aviation taxes have affected passenger growth in recent European policy interventions. The consistent pattern across all sensitivity tests - that estimated effects remain statistically insignificant - reinforces confidence in our main conclusion: **recent ticket taxes in France, Germany, the Netherlands and the UK have, according to our methodology, not measurably curbed air travel demand.**

Economic analysis finds no clear evidence that ticket taxes reduced passenger traffic

Each dot represents one model configuration. Statistical significance indicates confidence that the result is not due to random chance

Statistical power ● Statistically significant at 10% ● Statistically significant at 5% ● Statistically significant at 1% ● FALSE



Source: T&E analysis based on OAG, OECD and Eurostat • Differences-in-Differences strategy with airport and time fixed effects. Holm-Bonferroni sequential correction method. Extended control group, and all departing passengers from the country.



Annex II: Detailed results per country

Dutch air passenger tax

The Netherlands [tripled](#) its flat-rate aviation ticket tax from €7.45 to €26.43 in January 2023. Despite being the largest tax increase in our study, our analysis finds no statistically significant evidence that it reduced air travel demand.

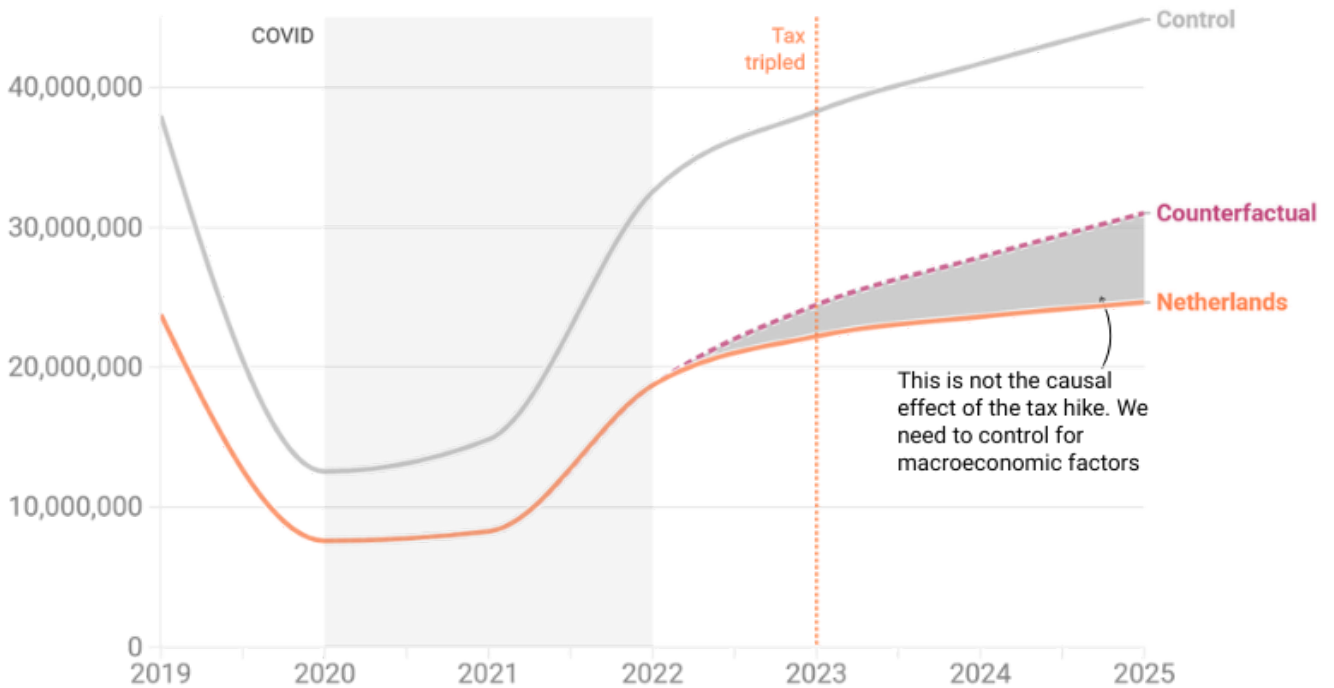
Tax	Flat rate
Dutch air passenger tax	€26.40

Overview of the Dutch flat-rate aviation tax introduced in January 2023

Following the 2023 tax hike, Dutch air travel continued its post-pandemic recovery but showed some signs of relative weakness. We estimated that total passengers in 2023 were still about -6% below 2019 levels. Some industry stakeholders [claimed](#) the steep tax prompted travelers to alter their behavior, particularly by shifting to airports in neighboring countries (a "leakage effect"). A recent [study](#) by the Ministry of Infrastructure and Water Management has already refuted this claim. Our econometric analysis is designed to test whether such behavioral changes were statistically detectable in aggregate passenger data.

Aviation traffic in the Netherlands grew slower than in un-taxed peer countries

Passenger trends before controlling for macroeconomic factors



Source: T&E modeling based on OAG data



Our analysis finds no statistically robust evidence that the Dutch tax reduced passenger volumes. Point estimates across different model specifications range from 5% to 7% reductions, but all remain statistically insignificant with p-values between 0.15 and 0.35. When we apply [conservative statistical methods](#), significance levels weaken further and disappear. This means we cannot confidently distinguish the observed pattern from random variation or other confounding factors affecting Dutch aviation during this period.

Regression results: Difference-in-differences estimated tax effect on departing passengers across model specifications (Netherlands, 2022-2025)

OLS regression results across six model specifications (M0–M5), showing the estimated effect of the air passenger tax on log passenger volumes for all departures from Dutch airports from January 2022.

Model specification	(0)	(1)	(2)	(3)	(4)	(5)
Key coefficient of interest						
Tax effect (β)	-0.0672	-0.0670	-0.0486	-0.0657	-0.0521	-0.0707
	(0.0479)	(0.0494)	(0.0523)	(0.0495)	(0.0521)	(0.0493)

Model specification	(0)	(1)	(2)	(3)	(4)	(5)
<i>Note: Airport and time fixed effects included in all models but coefficients omitted for brevity.</i>						
Intercept						
Constant	10.2087***	9.6960***	10.3265***	9.7466***	8.8657***	7.7670**
	(0.0362)	(3.3863)	(0.1242)	(3.3745)	(0.9587)	(3.6427)
Model fit statistics						
Adjusted R ²	0.976	0.976	0.976	0.976	0.976	0.976
Observations (N)	6,647	6,647	6,647	6,647	6,647	6,647
Controls included						
Airport fixed effects	✓	✓	✓	✓	✓	✓
Month-Year fixed effects	✓	✓	✓	✓	✓	✓
GDP per capita	–	✓	–	✓	–	✓
Unemployment	–	✓	✓	✓	✓	✓
Fuel prices	–	–	–	✓	✓	✓
Tourism	–	–	–	–	✓	✓
Airport fixed effects	✓	✓	✓	✓	✓	✓

T&E (2026). Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are used across all four model specifications.

Robustness checks

To verify that our findings do not depend on specific methodological choices, we conducted several sensitivity analyses. We tested [different proximity exclusion](#) rules to assess whether potential cross-border traffic shifts affect the results and we tested an [alternative control group composition](#) to ensure findings are not driven by specific country selection.

Across all robustness specifications, the pattern remains consistent: point estimates are negative but modest and none reach statistical significance under conservative testing. This confirms that the lack of detectable impact is not an artifact of our specific methodological choices regarding border airports or control group composition.

Several concurrent factors complicate the interpretation of Dutch aviation trends during this period. Capacity constraints at Amsterdam Airport Schiphol from flight caps, noise mitigation measures and staffing shortages all affected passenger volumes independently of the ticket tax. The post-pandemic recovery itself followed different trajectories across European countries for reasons unrelated to taxation policy. Our models attempt to control for these factors, but residual noise remains.

The lack of statistical significance does not mean the tax had zero effect. It means any effect is too small to measure reliably given the available data and the volatile market conditions. The true impact could range from a modest reduction to no behavioral change at all. What we can say with confidence is that the effect, if it exists, falls far short of the dramatic declines some industry stakeholders predicted. Dutch aviation continued growing in 2023 and 2025, albeit perhaps slightly more slowly than it might have without the tax, but we cannot confirm even that modest claim with statistical certainty.

UK Air Passenger Duty

In April 2023, the United Kingdom [reformed](#) its Air Passenger Duty (APD), reducing the rate on domestic flights while increasing it on ultra-long-haul routes. Our analysis finds no statistically detectable effect on overall UK passenger traffic from this reform.

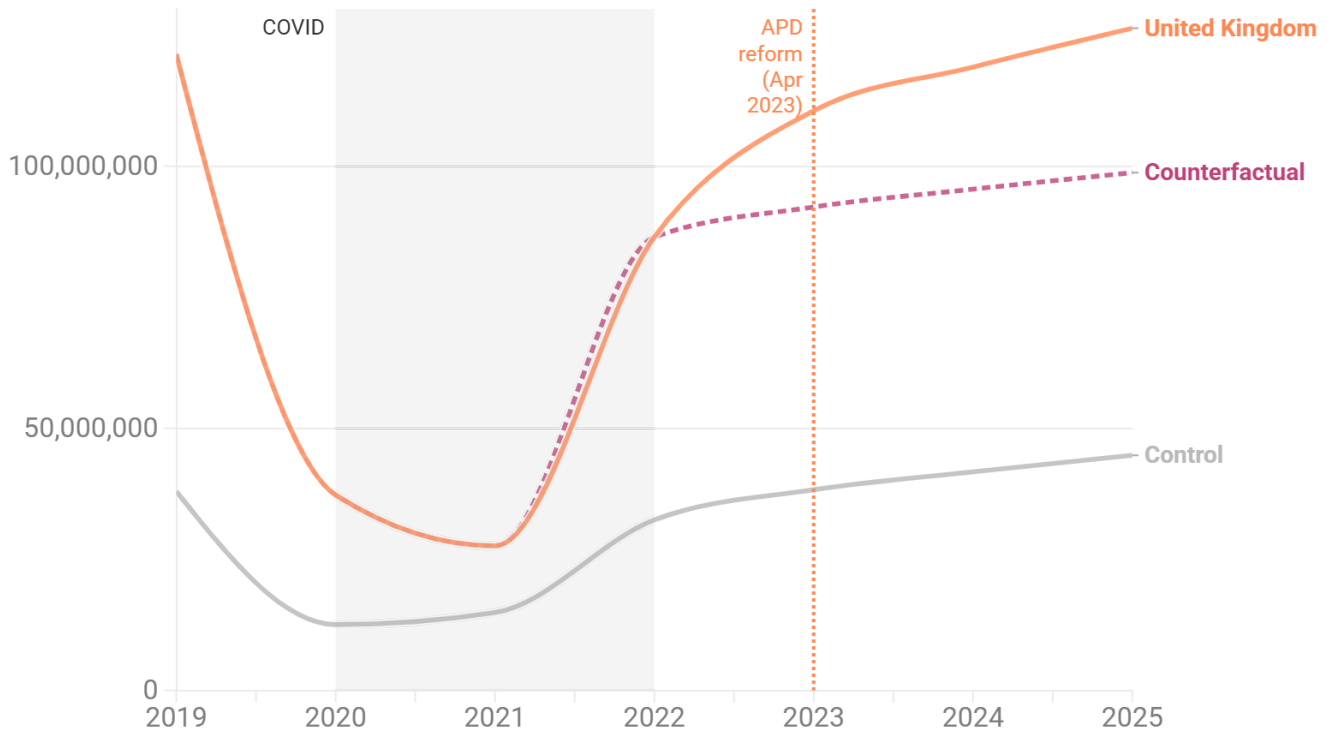
Distance band	Reduced rate (Economy class)	Standard rate (Business class)
Domestic	£6.50	£13
Band A	£13	£26
Band B	£87	£191
Band C	£91	£200

Overview of the UK Air Passenger Duty rates from April 2023

By 2023, UK air passenger traffic was recovering from pandemic lows (approximately 27% below 2019 levels) and continued climbing steadily through 2024-2025. The APD reform produced no visible deviation from this recovery trajectory. UK airports continued closing the gap to pre-pandemic volumes regardless of the tax adjustment.

Aviation traffic in the United Kingdom outpaced baseline growth

Passenger trends before controlling for macroeconomic factors



Source: T&E modeling based on OAG data



Our regression analysis confirms this visual impression. Point estimates are small and hover near zero, with large uncertainty. All specifications yield p-values well above conventional significance thresholds ($p > 0.26$). We cannot detect any systematic change in UK passenger volumes attributable to the APD reform.

Regression results: Difference-in-differences estimated tax effect on departing passengers across model specifications (United Kingdom, 2022-2025)

OLS regression results across six model specifications (M0–M5), showing the estimated effect of the air passenger tax on log passenger volumes for all departures from UK airports from January 2022.

Model specification	(0)	(1)	(2)	(3)	(4)	(5)
Key coefficient of interest						
Tax effect (β)	0.0093	0.0153	0.0338	0.0150	0.0530	0.0404
	(0.0456)	(0.0487)	(0.0487)	(0.0487)	(0.0473)	(0.0471)
<i>Note: Airport and time fixed effects included in all models but coefficients omitted for brevity.</i>						
Intercept						

Model specification	(0)	(1)	(2)	(3)	(4)	(5)
Constant	10.2224***	8.9016***	10.3197***	8.9399***	8.9332***	6.4923*
	(0.0341)	(3.2892)	(0.1066)	(3.2790)	(0.6575)	(3.3670)
Model fit statistics						
Adjusted R ²	0.981	0.981	0.981	0.981	0.981	0.981
Observations (N)	8,897	8,897	8,897	8,897	8,897	8,897
Controls included						
Airport fixed effects	✓	✓	✓	✓	✓	✓
Month-Year fixed effects	✓	✓	✓	✓	✓	✓
GDP per capita	–	✓	–	✓	–	✓
Unemployment	–	✓	✓	✓	✓	✓
Fuel prices	–	–	–	✓	✓	✓
Tourism	–	–	–	–	✓	✓
Airport fixed effects	✓	✓	✓	✓	✓	✓

T&E (2026). Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are used across all four model specifications.

Robustness checks

We tested whether results are sensitive to [proximity exclusion](#) rules and [control group composition](#). The estimates cluster around zero, and no specification reaches statistical significance. Because findings that lack statistical significance do not allow us to reach any conclusions, we cannot infer the exact impact of the adjustments to the UK Air Passenger Duty.

Lowering the duty on domestic flights while raising it on long-haul routes produced no statistically significant response in our current model. We cannot reliably isolate the impact of the tax structure from broader economic conditions like pandemic recovery dynamics and general ticket prices.

German Aviation Tax

Germany [raised](#) its aviation tax by approximately 22% in May 2024, raising rates from €12.74 to €15.53 on short-haul flights, €31.60 to €39.34 on medium-haul and €57.93 to €70.83 on long-haul routes. Our analysis finds no evidence that this increase reduced passenger volumes. In fact, several model specifications produced counterintuitive positive estimates.

Distance band	Rate
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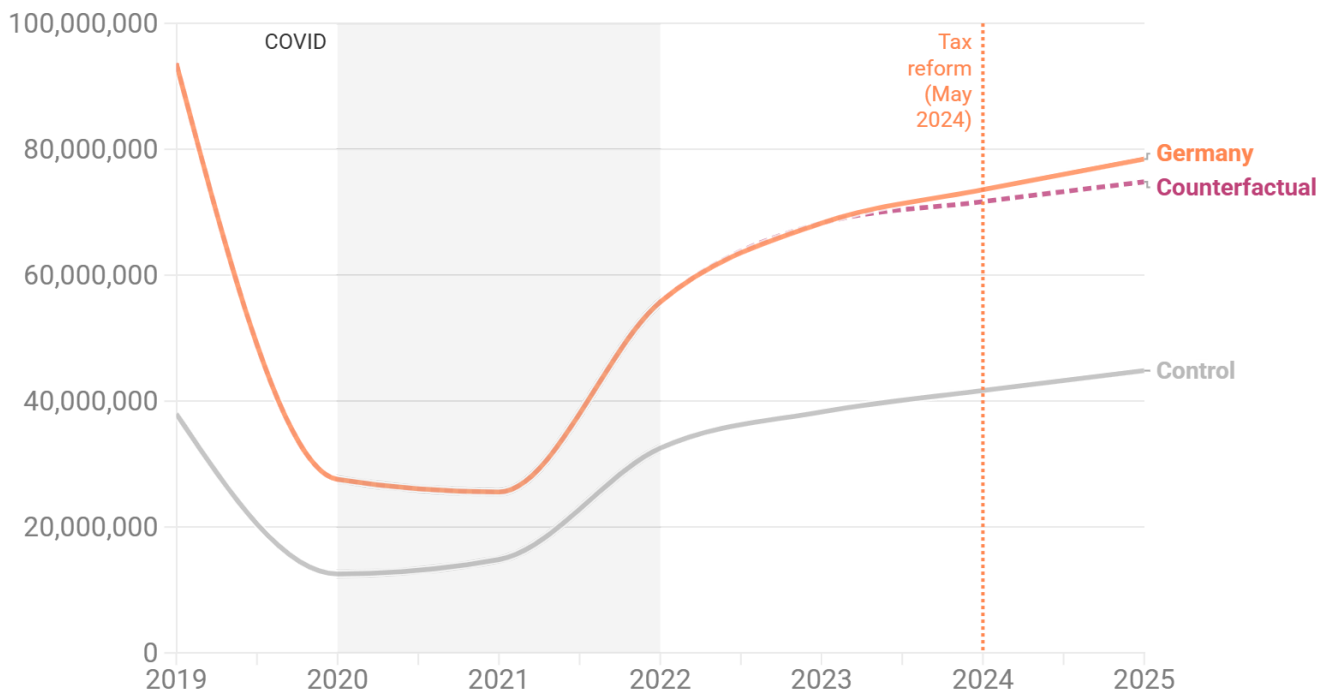
Domestic and short-haul flights	€15.53
Medium-haul flights (< 6,000 km)	€39.34
Long-haul flights (> 6,000 km)	€70.83

Overview of the German Aviation Tax rates from May 2024

Germany's air travel market in 2023-2024 was recovering more slowly than most other large European countries. By end-2023, German airports handled approximately 27% fewer passengers than in 2019, a larger shortfall than France (down 1%) or the UK (down 9%). This lag reflected structural factors including slower recovery of business travel demand and reduced Asian connectivity rather than taxation policy. Against this backdrop, the May 2024 tax increase coincided with continued growth as recovery progressed.

German aviation traffic showed no significant change following the recent ticket tax hike

Passenger trends before controlling for macroeconomic factors



Source: T&E modeling based on OAG data



Our regression analysis produces point estimates ranging from +9.6% to +12.1%, with several specifications reaching conventional 10% significance levels. However, these results fail under conservative statistical testing (bootstrap p-values exceed 0.19 in all cases). More importantly,

the positive sign contradicts economic theory and common sense; a tax increase should not stimulate demand.

Regression results: Difference-in-differences estimated tax effect on departing passengers across model specifications (Germany, 2022-2025)

OLS regression results across six model specifications (M0–M5), showing the estimated effect of the air passenger tax on log passenger volumes for all departures from German airports from January 2022.

Model specification	(0)	(1)	(2)	(3)	(4)	(5)
Key coefficient of interest						
Tax effect (β)	0.1178*	0.1127	0.1282*	0.1126	0.1298*	0.1139*
	(0.0676)	(0.0686)	(0.0730)	(0.0686)	(0.0729)	(0.0685)
<i>Note: Airport and time fixed effects included in all models but coefficients omitted for brevity.</i>						
Intercept						
Constant	10.1438***	11.4432***	10.1890***	11.4964***	9.8498***	10.9618***
	(0.0382)	(3.3758)	(0.1266)	(3.3672)	(1.0032)	(3.7677)
Model fit statistics						
Adjusted R ²	0.973	0.973	0.973	0.973	0.973	0.973
Observations (N)	7,384	7,384	7,384	7,384	7,384	7,384
Controls included						
Airport fixed effects	✓	✓	✓	✓	✓	✓
Month-Year fixed effects	✓	✓	✓	✓	✓	✓
GDP per capita	–	✓	–	✓	–	✓
Unemployment	–	✓	✓	✓	✓	✓
Fuel prices	–	–	–	✓	✓	✓
Tourism	–	–	–	–	✓	✓
Airport fixed effects	✓	✓	✓	✓	✓	✓

*T&E (2026). Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are used across all four model specifications.*

Robustness checks

We tested [alternative proximity exclusions](#) and [control group specifications](#) to verify these counterintuitive findings. The pattern of positive, statistically insignificant estimates persists across sensitivity tests, confirming that the counterintuitive results reflect Germany's unique post-pandemic recovery trajectory rather than a genuine stimulative effect of taxation.

The positive estimates we observe underscore the methodological challenges of isolating small policy effects during volatile market conditions. Germany's recovery trajectory appears to have

diverged slightly upward relative to control countries in the post-May 2024 period. This likely reflects timing differences in business travel recovery or airline capacity decisions.

The 22% tax increase added only modest absolute amounts to ticket prices. However, our applied methods fail to measure the effects of this incremental cost amid strong pent-up demand. The lack of a statistically significant result means these findings do not tell us anything conclusive about passenger behavior.

French Solidarity Tax

France [increased](#) its "solidarity tax" on airplane tickets in March 2025, roughly doubling or tripling rates depending on route and cabin class. Our analysis finds no statistically significant evidence that this increase reduced passenger volumes, though we caution that only nine months of post-implementation data are available.

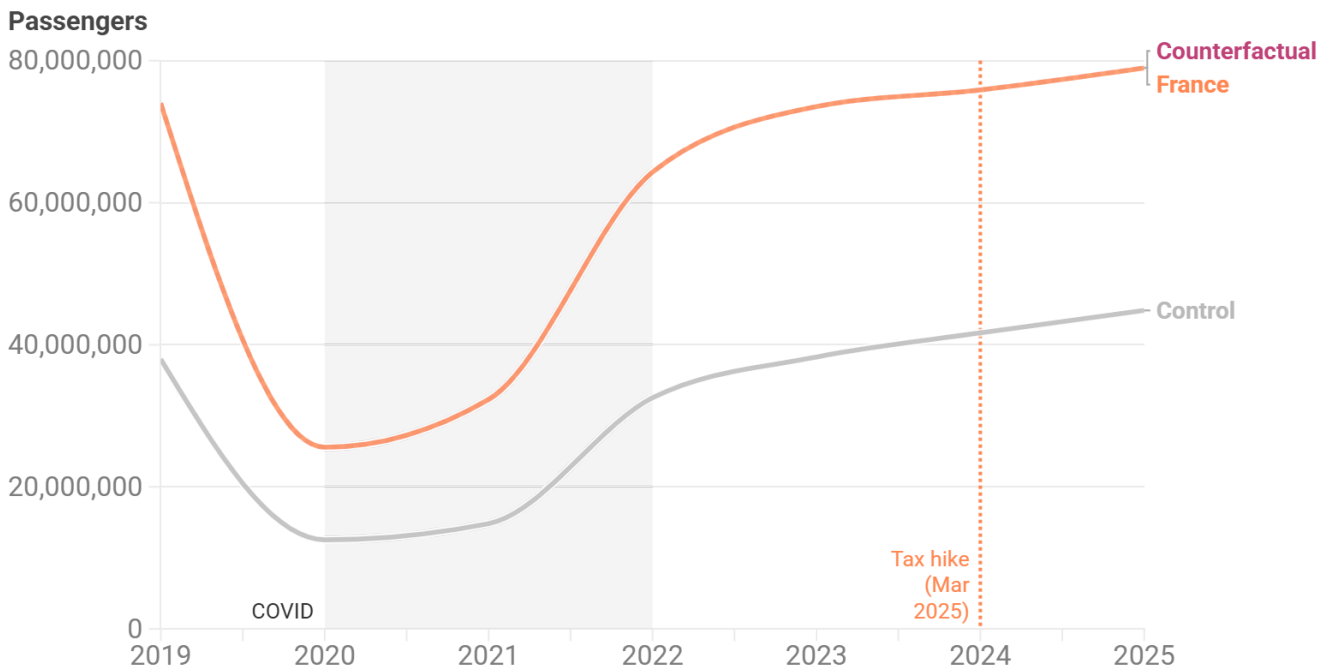
Distance band	Reduced rate (Economy class)	Standard rate (Business class)
European or similar destination	€7.40	€30
Intermediate destination (< 5,500 km)	€15	€80
Distant destination (> 5,500 km)	€40	€120

Overview of the French Solidarity tax on airplane tickets from March 2025

By 2024, France's air passenger traffic had fully recovered to pre-pandemic levels, driven by strong leisure travel demand. The March 2025 tax increase produced no obvious deviation from this growth trajectory. French airports continued seeing healthy traffic levels through late 2025.

It is too early to detect the impact of the March 2025 French ticket tax increase

Passenger trends before controlling for macroeconomic factors



Source: T&E modeling based on OAG data



Our difference-in-differences analysis produced negative point estimates ranging from 3% to 7%, but all remain statistically insignificant with p-values between 0.11 and 0.49. This means we cannot confidently distinguish any observed pattern from normal market variation. The limited post-implementation period (only ten months of data through December 2025) substantially constrains our ability to detect effects even if they exist.

Regression results: Difference-in-differences estimated tax effect on departing passengers across model specifications (France, 2022-2025)

OLS regression results across six model specifications (M0–M5), showing the estimated effect of the air passenger tax on log passenger volumes for all departures from French airports from January 2022.

Model specification	(0)	(1)	(2)	(3)	(4)	(5)
Key coefficient of interest						
Tax effect (β)	-0.0862*	-0.0893*	-0.0588	-0.0886*	-0.0566	-0.0877*
	(0.0479)	(0.0492)	(0.0497)	(0.0491)	(0.0497)	(0.0492)
<i>Note: Airport and time fixed effects included in all models but coefficients omitted for brevity.</i>						

Model specification	(0)	(1)	(2)	(3)	(4)	(5)
Intercept						
Constant	10.1662***	11.0469***	10.3046***	11.1086***	9.0069***	9.4287***
	(0.0389)	(3.2892)	(0.1158)	(3.2782)	(0.8788)	(3.5301)
Model fit statistics						
Adjusted R ²	0.974	0.974	0.974	0.974	0.974	0.974
Observations (N)	7,921	7,921	7,921	7,921	7,921	7,921
Controls included						
Airport fixed effects	✓	✓	✓	✓	✓	✓
Month-Year fixed effects	✓	✓	✓	✓	✓	✓
GDP per capita	–	✓	–	✓	–	✓
Unemployment	–	✓	✓	✓	✓	✓
Fuel prices	–	–	–	✓	✓	✓
Tourism	–	–	–	–	✓	✓
Airport fixed effects	✓	✓	✓	✓	✓	✓

T&E (2026). Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are used across all four model specifications.

Robustness checks

We tested whether [proximity exclusions](#) and [control group composition](#) affect the findings. Results remain consistent across all specifications: negative point estimates in the range of 3% to 8%, but consistently statistically insignificant. The lack of detectable impact is robust to methodological choices.

France's ticket tax increase adds modest absolute amounts to most routes. Even after the March 2025 hike, the tax adds only €7.40 to intra-European economy tickets and €15 to intermediate destinations. While French air travel shows strong continued growth, the current data and model do not support the argument that there is a statistically significant result. Our analysis lacks the statistical power to confirm if the policy change caused a small demand reduction. We cannot infer anything about the relationship between the tax and travel demand from these findings. Clearer patterns may emerge as more data become available in 2026.

Further information

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