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Did the German aviation tax have a lasting effect on passenger numbers?

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ABSTRACT

The taxation of aviation is a frequently discussed component of governments' efforts to mitigate greenhouse gas emissions. This study examines the impact of the German aviation tax on passenger numbers during the period 2011–2019 using five panel data estimators and a Specification Curve Analysis (SCA) to assess the robustness of the results to changes in the specifications of the econometric model. Employing five base models, we find that the tax induced a 6–11% reduction in the number of passengers departing annually from Germany in the first two years after implementation. For later years, estimated effects are more ambiguous. The SCA, comprising 175 alternative specifications, corroborates our main findings while showing a slightly wider range of effect sizes, especially on the upper bound. The results show that the choice of econometric method can affect research outcomes, especially for the fourth year of the tax and onward.

1. Introduction

Greenhouse gas emissions from the aviation sector are rising and of growing concern to scientists and policymakers. From 2005 to 2019, passenger-kilometers flown with commercial flights, departing from the 28 countries in the European Union (EU) and from the European Free Trade Area, have increased by 90%, while resulting CO_2 emissions increased by 34% (EASA 2022). By comparison, EU CO_2 emissions from fossil fuel use overall declined by 5% over the same period. The COVID-19 pandemic temporarily curbed growth in the aviation sector, but recovery is well underway, with the number of flights within and out of Europe in 2023 at 92% relative to 2019, with the numbers expected to fully catch up in 2024 (Eurocontrol 2024a). Indeed, projections estimate that the number of flights will continue growing steadily (Eurocontrol 2024b). Importantly, the climate change impacts from aviation do not stem from CO_2 emissions alone; Lee et al. (2021) conclude that non-CO_2 impacts (from nitrogen oxides, water vapor, soot, sulfate aerosols and contrail formation) comprise about two-thirds of the sector's climate impact this century.

Air passenger taxes can mitigate aviation's contribution to global warming by increasing the price of flight tickets, while simultaneously increasing the efficiency of the tax system by broadening a country's tax base (Krenek and Schratzenstaller 2017). Currently (in 2024), per-passenger aviation taxes are levied in nine European countries, including the United Kingdom, which introduced an air passenger duty in 1994; France, which introduced a civil aviation tax in 1999; and Germany, which introduced an air passenger tax in 2011. At the EU level, the aviation sector was included in the Emission Trading Scheme (EU ETS) in 2012, but only for emissions of intra-EU flights. The merits of aviation taxes are hotly debated, and the 2011 German aviation tax received ample attention from the

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public, as can be clearly seen when consulting Google Trends.[1] Professional opinions are divided, with environmental groups arguing that the tax is insufficient – or insufficiently high – to adequately reduce the sector's emissions, and industry representatives arguing that it leads to job and GDP losses (BUND 2013, Transport and Environment 2021, IATA 2010, PwC 2017).

In this paper, we contribute to this debate by investigating the impact of the German aviation tax on the number of passengers who departed from German airports between 2011, the year of the tax's inception, and 2019. We conduct an event study analysis employing a range of panel data models, in which the treated group comprises all German airports and the control group consists of airports in EU countries without an air passenger tax.

Earlier assessments of the German aviation tax typically applied one econometric model and only one or two model specifications (Gurr and Moser 2017, Borbely 2019, Falk and Hagsten 2019). We present results for five different econometric estimators and various model specifications comprising 175 alternative, yet equally plausible, combinations of estimators and model specifications. This enables us to assess the robustness of our main results. We show that the choice of the econometric estimator affects the estimates of the effects of the tax. Hence, the robustness of policy evaluations could be improved by applying a wider range of (plausible) econometric estimators and model specifications.

The remainder of the paper is organized as follows. The next section reviews the current literature on the topic of aviation and taxation. Section 3 presents some background on the German aviation tax. Section 4 describes the methods and data used. Section 5 presents the results of our main regression specifications and Section 6 presents the results from the Specification Curve Analysis. In Section 7 we discuss our findings and we conclude in Section 8.

2. Literature review

On the whole, the ex-post impact assessment literature contains mixed results for aviation taxes. Seetaram et al. (2014) analyze the effects of changes in the UK Air Passenger Duty on the total number of outbound passengers to ten countries using country-specific time series models. They conclude that the UK Duty reduced demand for travel to five out of the ten analyzed destinations, with taxation elasticities smaller than one. Markham et al. (2018) use time series analysis to determine the effects of a levy on CO_2 emissions from Australia's 2012–2014 Clean Energy Future policy on domestic aviation. They found no effect from the levy. González and Hosoda (2016) use time series analysis to analyze the impact of the 30% tax rate cut introduced in 2011 in Japan, which had been taxing fuel since 1972. In 2013, following the tax cut, emissions from domestic flights had increased by 9.23% compared to the scenario of no tax change. For the German aviation tax, Gurr and Moser (2017), through a panel data analysis without a control group, find that each Euro of tax reduces the number of passengers departing from Germany by 0.2%. Borbely (2019) applies the synthetic control method to individual airports located in Germany and foreign airports close to the German border. He finds that the average impact of the tax over the period 2011–2013 varies strongly across airports, with an increase in passenger numbers of up to 15% for five out of six large German airports, and decreases of up to 37% for almost all regional airports. Falk and Hagsten (2019) use a dynamic panel difference-in-differences model to analyze the joint effect of the German and Austrian aviation taxes. They conclude that the short-run effect of the tax was a reduction in the total number of passengers of 9% in the year of introduction, and a reduction of 5% in the year thereafter. They show that their results are mainly driven by airports used predominantly by low-cost airlines, while large hub airports appear not to have been affected by the tax. Bernardo et al. (2024) study the joint average impact of the German, Austrian, Swedish and Norwegian passenger taxes on the number of flights using a staggered difference-in-differences approach. They find a reduction in the number of flights of 12% for low-cost airlines, and a reduction of 5% when taking into account all airlines.

Earlier assessments of passenger taxes typically applied one econometric model and only a few model specifications. Our contribution lies in the systematic way in which we aim to determine the tax's effect. First, we introduce three different econometric models with five different estimators. Each model and estimator has its own merit in assessing the impact of an aviation tax. Applying all five estimators allows us to assess how the results are affected by estimator choice, while acknowledging that there is no objectively correct choice. Secondly, we employ a Specification Curve Analysis (SCA) (Simonsohn et al. 2020) to evaluate the robustness of our estimates. In addition to choosing an estimator for the assessment of the effect of the tax, researchers can make numerous other choices in research design that can affect the results, such as selection of the treatment and control group, the data subset, and the included covariates. An SCA allows us to assess whether particular model specifications lead to smaller or larger effect estimates relative to other specifications. As with the choice of model estimator, there are a number of ways to choose covariates and to delineate the sample of airports used. The SCA makes the range and effects of these choices explicit. With the SCA we can also more robustly evaluate both the existence and magnitude of the effect of the tax on passenger numbers for each year in the evaluated period. Third, we assess the effect of the tax for each of the first nine years after its introduction in 2011, a longer time frame than previous studies, and explicitly address the parallel trends assumption through empirical means. Finally, we explicitly acknowledge the identification difficulties that arise from using hub airport data for a research question such as this one and address them, at least in part, by running our estimations additionally with a clearly delineated sub-sample of non-hub airports.

3. Background

The German aviation tax entered into force on January 1st, 2011. The aim of the tax was threefold: to generate additional tax

[1] See Google Trends results when searching for the terms "Luftverkehrs(s)teuer" and "Flugsteuer" in and around 2010, see for example: https://trends.google.com/trends/explore?date=2005–01-01%202020–12-31&geo=DE&q=Luftverkehrsteuer,Flugsteuer,Luftverkehssteuer.

income, to end the exemption of air travel from mobility taxes, and to create incentives for environmentally friendly behavior. The tax applies to outbound passengers and is payable by the carrier airline for each seat sold for each flight departing from Germany. The tax does not apply to passengers who started their journey outside of Germany. Those not taxed include *transfer* passengers, who started their journey outside of Germany and switch flights in Germany during their journey, and *transit* passengers, who started their journey outside Germany and continue their journey in Germany on the same aircraft, usually with the same flight number. The tax is split into three rates based on the distance zone in which the journey ends according to the ticket purchased. Zone 1 includes flights to all EU Member States and candidates as well as EFTA members and other countries that have their main airport within this radius, notably Türkye, Russia, Morocco, Tunesia and Algeria. Zone 2 includes countries that are not located in zone 1 but whose main airport lies within a distance of 6,000 km of Germany. Zone 3 finally comprises all remaining countries. A map of the three distance zones can be found in Fig. A1 in Appendix A. In 2011, the tax rates were €8.00, €25.00, and €45.00 for distance zones 1, 2 and 3, respectively. Since then, the rates have, on average, increased by a rate equal to the increase in the consumer price index for zones 2 and 3, and by slightly more than that for zone 1.

As mentioned, only those passengers who start their journey at a German airport are subject to the tax. The basis for taxation is the full journey purchased by a passenger. A particularly savvy traveler who considers a journey with layovers outside Germany might try to circumvent having to pay part of the tax by booking tickets for the parts of their journey outside Germany separately. However, the tax is not transparently applied for consumers and is typically not shown explicitly when purchasing a ticket; it is only listed on the more detailed receipt issued at the end of a purchase process. Since there are also important benefits to booking a journey in one go (e.g. being eligible for compensation when a previous flight was delayed), it can be assumed that tax circumvention of this kind is not common practice. A visual representation of the large number of different types of journeys booked (Fig. A2) can be found in Appendix A.

4. Methods and data

4.1. Econometric models

The structure of our data lends itself to several possible estimators depending on the assumptions made about the data generation process. Since it is difficult to a priori glean which econometric approach is the most suitable, we employ a range of estimators.

Our point of departure is a Two-Way Fixed Effects (TWFE) specification, given by Equation (1):

$$\ln(pax_{it}) = \beta_0 + \sum_{s=2006}^{2009} \beta_s^{pre} d_{it}^{s-treat} + \sum_{s=2011}^{2019} \beta_s^{post} d_{it}^{s-treat} + \beta_x^T X_{it} + \tau_t + \mu_i + \varepsilon_{it} \tag{1}$$

where $\ln(pax_{it})$ indicates the natural logarithm of the number of departing passengers at airport i in year t, $d_{it}^{s-treat}$ are treatment dummies for each year s, X_{it} is a vector of time-varying explanatory variables, τ_t are the year fixed effects, μ_i are the time-invariant airport fixed effects, and ε_{it} is the error term. Dummy $d_{it}^{s-treat}$ is set to 1 if airport i is treated – meaning it is located in Germany – and if $t = s$. For the years 2006–2009 these dummies are pre-treatment dummies that allow us to test whether the number of passengers at German airports significantly differed from those in the control group before treatment took place (Abadie 2005, Callaway and Sant'Anna 2021). To avoid multicollinearity, the dummy needs to be dropped for one year. We did this for the year 2010, which therefore serves as the reference year. The dummies for the years 2011 to 2019 are the variables of interest. Their coefficients β_s^{post} record the effects of the implementation of the German aviation tax in each of the years 2011 to 2019. The airport fixed effects address potential omitted variable bias that stems from unobservable time-invariant airport-specific characteristics, while the year dummies control for shocks that affected all airports in the sample in the respective year. Assuming time-constant unobserved heterogeneity, this will lead to consistent estimates (see e.g. Wooldridge 2013, Cameron and Trivedi 2005, Greene 2012).

The dependent variable – the logged annual number of passengers departing from an airport – is likely to have a high level of persistence. For example, changes in an airport's capacity or in its use by carriers carry over from one year to the next, and airlines' decisions – such as the frequency of flights offered or the number of seats available on each flight – are made based on past years' passenger numbers. The remaining models in our analysis therefore include a lagged dependent variable. We still report the results for the static TWFE because it is the cornerstone model for panel data, but persistence in passenger numbers may result in an overestimation of the true effects with the static TWFE model (Angrist and Pischke 2009, p.246).

Our second model includes a lagged dependent variable and discards the airport-fixed effects, as shown in Equation (2):

$$\ln(pax_{it}) = \beta_0 + \beta_1 \ln(pax)_{i,t-1} + \sum_{s=2006}^{2009} \beta_s^{pre} d_{it}^{s-treat} + \sum_{s=2011}^{2019} \beta_s^{post} d_{it}^{s-treat} + \beta_x^T X_{it} + u_{it} \tag{2}$$

We estimate model (2) using a pooled OLS estimator. For analyses using panel data, in which both a static approach with fixed effects (equation (1)) and a dynamic approach without fixed effects (equation (2)) have merit, existing literature has shown that even though the "true" model often cannot be definitively determined (i.e. whether including fixed effects or including a lagged dependent variable is more appropriate), estimates from the two approaches tend to bracket the "true" effect (Angrist and Pischke 2009). One virtue of referencing the two models jointly is, hence, that through this bracketing relationship, it can provide a reference point for the range of reasonable estimates of the causal effect.

Finally, a dynamic fixed effects model combines the properties of the two models above, as shown in Equation (3):

$$\ln(pax_{it}) = \beta_0 + \beta_1 \ln(pax)_{i,t-1} + \sum_{s=2006}^{2009} \beta_s^{pre} d_{it}^{s\_treat} + \sum_{s=2011}^{2019} \beta_s^{post} d_{it}^{s\_treat} + \beta_x^T X_{it} + \tau_t + \mu_i + \nu_{it} \quad (3)$$

In our analyses we use data for the period 2005–2019. This time window is neither very long (in which case the bias from including a lagged dependent variable (Nickell 1981) would disappear) nor very short. Hence, we use estimation methods for short time dimensions and for long time dimensions. We estimate Equation (3) using a simple fixed effects estimator to cover the case of a long time dimension. In addition, we use the Arellano-Bond estimator (Arellano and Bond 1991) and the quasi-maximum likelihood estimator developed by Kripfganz (2016) for dynamic fixed effects models to cover the case of a short time dimension. The results from the various econometric models will provide a range of estimates in which the true β_t^{post} can be expected to be located. All models are estimated using Stata 16 software.

4.2. Model specifications

In addition to presenting the results from five different estimators, there were a number of decisions concerning the final specifications, including which airport (types) to include, the treatment of air fare price as a variable, the inclusion of dummies for pre-treatment years and neighboring airports, and which sub-sample of the data to use. We detail below which choices were made for the main specifications, and we report results from a range of other combinations in our robustness test via Specification Curve Analysis (SCA).

As mentioned above, the German aviation tax only applies to passengers who start their journey at a German airport; that is, transfer passengers are not subject to the tax. Since the data on departing passengers do not distinguish transfer passengers from others, data for German hub airports include large numbers of passengers that are not subject to the tax. For example, Munich airport has estimated that 38% of its departing passengers in 2019 were transfer passengers, while Frankfurt airport puts this at 53.7% for the same year (Munich Airport 2021, p. 10; Fraport 2019, p. 11). This means that more than a third of passengers at Munich, and more than half at Frankfurt, were not taxed for their journey departing from the airport. Including hub airports in the data will give estimates of the effect of the tax on the *total* number of passengers departing from German airports, including those who did not actually have to pay the tax. When excluding international hubs from the data, the estimated coefficients β_t^{post} will provide a better estimate of the effect of the tax on those passengers *who are actually subject to the tax* (i.e., who start their journey in Germany), but will, however, not cover the entirety of the German aviation market. We therefore report both results based on the full set of German airports and results based on data that exclude German and non-German hub airports (see Appendix B for a list of airports identified as hubs and Section 4.4 for the selection criteria) to set up a solid comparison. Following the same reasoning, Bernardo et al. (2024) looked at low-cost airlines separately, as well as looking at the market in its entirety, while Falk and Hagsten (2019) only looked at airports that serve low-cost carriers.

We also accounted for potential spillover effects of the tax. Passengers that live in Germany but are relatively close to a foreign airport, can avoid the tax by choosing the foreign airport over the German ones. This way, the German aviation tax could have led to an increase in passenger numbers at those foreign airports. If these airports are included in the control group, then the estimated effect of the tax on passengers departing from German airports might be biased downward. Our main analyses therefore exclude non-German airports that are within 350 km from the border with Germany (see also Borbely, 2018; Falk and Hagsten, 2019; see Appendix B for the list of airports identified as 'neighboring'). We do include them in the robustness analysis.

Estimates of the effect of the German aviation tax may be biased, however, if airports in the control group were subject to the introduction of, or significant changes in, an aviation tax in their own country. This applies to airports located in Austria, France, Ireland, Italy, the Netherlands, and the United Kingdom, all of which we excluded from our main specifications. We do include these countries in the robustness analysis.

Variation in ticket prices is commonly seen as a good predictor of ticket sales and therefore the number of passengers. However, the tax can be expected to be (partly) passed through to the passengers (Koopmans and Lieshout 2016). Including the price as a predictor of demand will lead to the problem of a "bad control" if, in an econometric model, one also includes a treatment dummy (Angrist and Pischke 2009, Wooldridge 2013, Imbens and Rubin 2015). Proposed solutions are either leaving the variable in question out of the equation entirely, or replacing it with a suitable proxy (King 1991, Angrist and Pischke 2009 pp. 64–68). For the main analyses, the former strategy was chosen. In our robustness testing, we did apply two different proxies and report the resulting effect estimates.

No further changes are made to the data subset used in our main models. We later check the robustness of our results to potential anomalies in the underlying dataset by testing the following changes in our robustness testing via SCA: only include airports that have data for all years (which leads to a balanced panel); drop the top and bottom 0.5% of observations with respect to passenger numbers; and including only the years 2007–2019, since some EU countries only began reporting the respective data to Eurostat after 2006.

4.3. Specification Curve analysis

We use a Specification Curve Analysis (SCA; Simonsohn et al. 2020) to present, compare and discuss the results of our robustness testing. Simonsohn et al. (2020) argue that the specifications executed and presented by a researcher are often subjective and at times encourage cherry-picking if the researcher elects to present only those estimations whose results are favorable to the primary

Table 1
Summary statistics of final data.

	Treated (Germany)		Control	
	Mean	St.D.	Mean	St.D.
Number of non-hub airports	17	–	246	–
Number of hub airports	4	–	22	–
Years	15		15	
Annual number of departing passengers per airport (million)	3.99	6.66	1.93	4.36
Annual number of departing passengers per airport, non-hub (million)	1.64	1.99	0.99	1.74
GDP per capita (1000 US$)	43.17	3.83	39.75	18.11
General transport index (HICP)	95.94	6.00	95.74	7.34
Kerosene price (US$/barrel)	77.67	3.88	162.19	152.29
Accomodation price (HICP, 2010 = 100)	88.61	13.28	99.03	10.53
Terror attack dummy	0.8	0.41	0.36	0.48
N	315		4020	

hypothesis. It is common practice to test alternative specifications and report them in the robustness test section of a paper. But even then, researchers can be inclined to only report favorable tests, even unintentionally. Given that there is limited room in a publication, researchers always have to make decisions on what model results they present, and which ones they exclude. Simonsohn et al.'s solution is to look at all the specification decisions that were made for the main models, collect all alternative, plausible, and non-redundant specifications, and then run these estimations and any useful combinations of them. The coefficient magnitudes and statistical significance values are then extracted from each individual regression, sorted by size, and presented in a plot. This visual representation facilitates the identification of relations between specification characteristics and regression outcomes. Moreover, it reduces opportunities for selective reporting, even if it will not eliminate the influence of a researcher's beliefs entirely (Simonsohn et al. 2020).

4.4. Data

For our estimation, we use annual data on departing passengers per airport, as provided by Eurostat (2021). The full dataset is comprised of 365 airports in 31 European countries spanning the years from 2005 to 2019. Data from 2020 onwards was not included due to the far-reaching effects of the COVID-19 pandemic on travel behavior.

Only airports without missing datapoints between 2009–2012 (i.e. around the introduction of the tax) were used for estimation. Following Borbely (2018), German and non-German airports that had major policy changes in the period of interest (e.g. a relatively small airport that started catering to a major tour operator) were excluded. Six such airports were identified in Germany and 13 in the control countries (see Appendix B for the list of eliminated airports).

To distinguish hub and non-hub airports, an airport is given the identifier "hub" if it meets at least one of the following criteria: a) it is an official hub of a non-low-cost carrier airline, b) it has regular flights to destinations outside Europe and Northern Africa, or c) it is the main international airport of a European country. We identified 26 European hubs, a list of which can be found in Appendix B. The dataset for our basic specification includes 289 airports, 26 of these hubs, in 27 European countries.

We include the following variables as covariates. We include GDP per capita (in US$ of 2021, World Bank 2021) since a positive effect of income on aviation travel is to be expected. As noted above, we do not include a proxy for ticket prices in our base specification to avoid the problem of having a "bad control". However, in our SCA we use two proxies. First, the price of kerosene (in US$ of 2021) was retrieved from the IEA energy prices database (International Energy Agency 2022). These data are not available for all countries in the sample, so its inclusion restricts the number of observations. The second proxy is a generalized Harmonized Index of Consumer Prices (HICP) for transport services (Eurostat 2021b). The HICP is an index of changes in consumer prices, recorded and collected by Eurostat for a large number of product groups and subgroups (such as transportation). In addition, we include a dummy for the occurrence of a terror attack (University of Maryland 2021)[2] and the HICP of accommodation services (Eurostat 2021b) as covariates. Table 1 provides the summary statistics for all variables.

5. Results

5.1. Parallel trends

The validity of our analysis is predicated on the assumption of parallel trends (see Angrist and Pischke 2009). Parallel trends are present if, in a scenario without the treatment, the treated and untreated group were to develop in parallel. Since this counterfactual cannot be observed, one frequently looks at the two groups' pre-treatment developments. As can be seen in Fig. 1, the development of

[2] Dummy for terror attacks was constructed using the 2007–2019 entries for Eastern and Western Europe from the Global Terrorism Database (University of Maryland 2020). For each country and year where an attack occurred that fulfilled all three "inclusion criteria" (University of Maryland 2021, pp. 16-17), the dummy was coded as "1″.

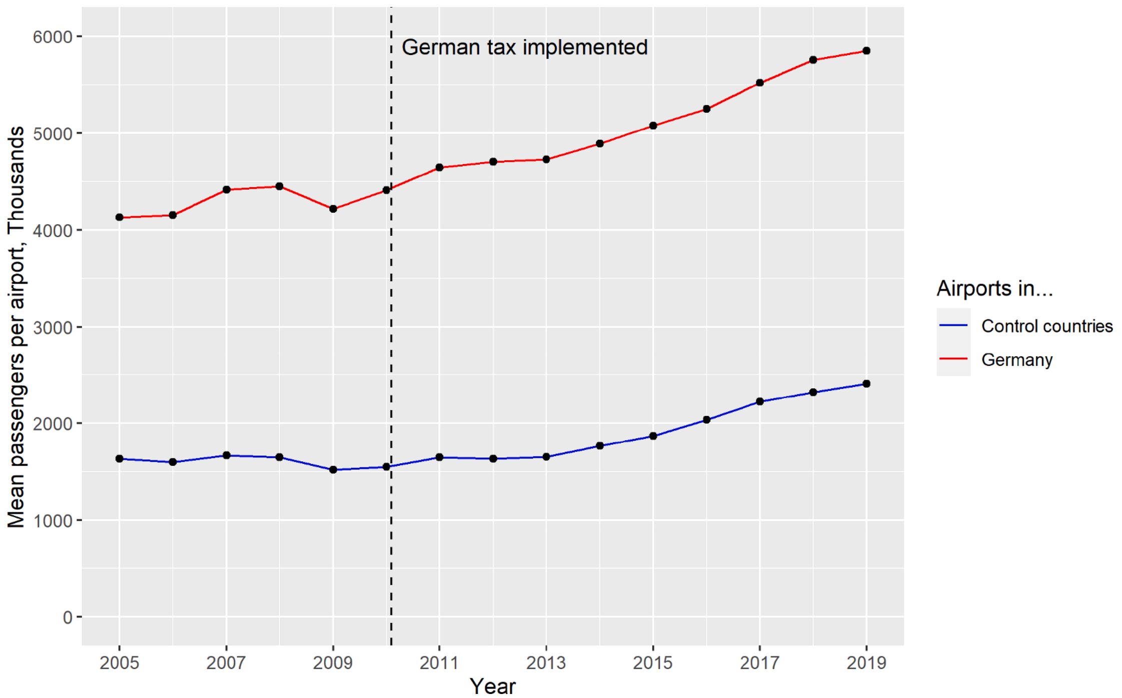

Fig. 1. Visual analysis of parallel trends for all airports. Mean annual number of passengers per airport in Germany (red) and the group of control countries (blue). Data: Eurostat (2021a).

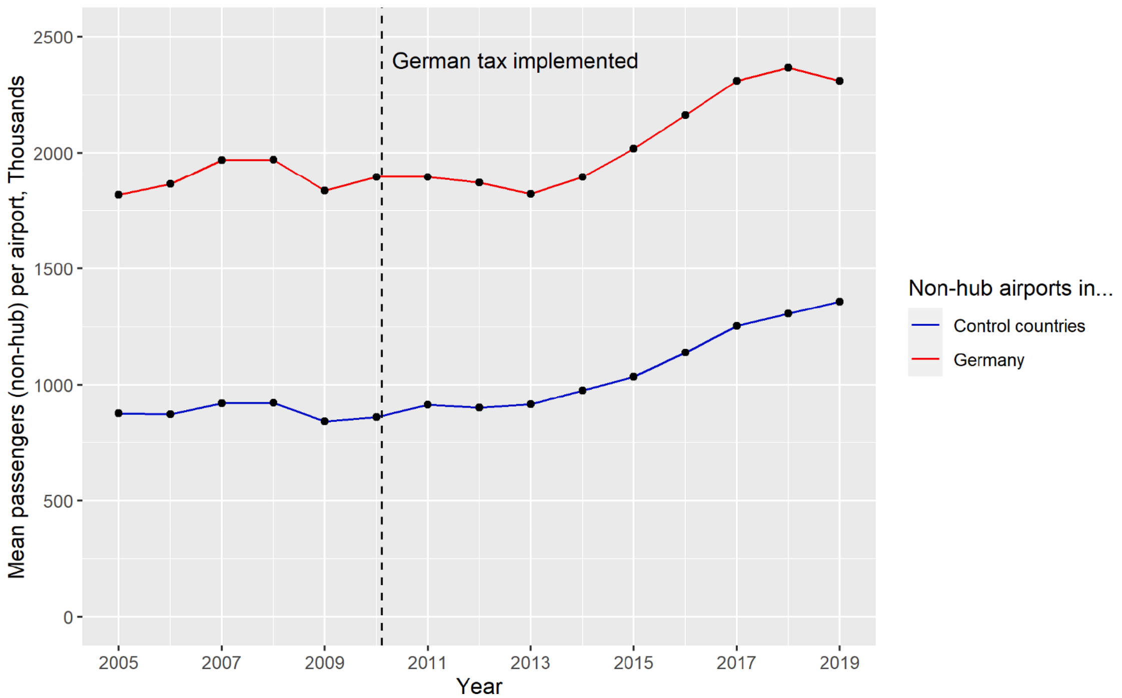

Fig. 2. Visual analysis of parallel trends for non-hub airports. Mean annual number of passengers per non-hub airport in Germany (red) and the group of controls (blue). Data: Eurostat (2021a).

the average number of passengers differs for the years 2006 and 2008. For non-hub airports, visual inspection suggests that there is a difference for the year 2006 (see Fig. 2). To check for the existence of parallel trends empirically, we include pre-treatment dummies in our regressions. Statistically significant pre-treatment dummies are only found for the dynamic TWFE model for 2006 and 2007 (for both groups of airports) and for the QML model for 2006 (only for the full sample of airports). We exclude the pre-treatment dummies from the results tables below for brevity.

These results are overall good indicators for the existence of parallel trends. For the full regression tables, including the coefficients for these pre-treatment dummies, see Appendix C, Table C6 and Table C7.

5.2. Regression results

We estimate Equations (1), (2), and (3) using the estimators presented in Section 3, with standard errors clustered at the country level where possible and robust standard errors where required by the estimator. When we report our results – the coefficients of the yearly treatment dummies – as percentage changes, we use the formula $\left(e^{\beta}-1\right) \times 100$, where β is the regression's estimated coefficient. Results are presented for the three econometric models presented in Section 4.1, using the following estimators: static Two-Way Fixed Effects (TWFE), pooled OLS with a lagged dependent variable, TWFE with a lagged dependent variable, Arellano-Bond, and Quasi-Maximum Likelihood (QML).

Table 2 shows the effects of the tax on the total number of passengers departing from German airports (i.e. when including all airports in the data set) for our main specifications. It should first be noted that the coefficients for the lagged dependent variable are rather large. In the case of the model based on pooled OLS with a lagged dependent variable (LDV), it is even larger than one, albeit not statistically significantly larger. LDV coefficients close or equal to one generally indicate a so-called "random walk" data generation process. The model using QML also results in an LDV coefficient which is very close to and not statistically different to one, while the other two dynamic models' LDV coefficients are smaller.

The coefficients are, as expected, largest (in absolute value) when using the static TWFE. Regarding the effects of the tax, all models find a significant decrease in passenger numbers for 2011, with the estimated effect size ranging from −7% to −11%. Only the static TWFE model and the dynamic TWFE model find significant effects in 2012, of −11% and −6% respectively. The static TWFE and dynamic TWFE models find a statistically significant effect of the tax for later years; these report statistically significant coefficients from 2018 and 2016 on, respectively.

Table 3 presents regression results using data from non-hub airports only. Again, coefficients of the lagged dependent variable (LDV) are large, with those of the POLS + LDV and QML estimates being statistically equal to one and the rest being lower. Regarding

Table 2
Results for sample including all airports. Dependent variable is log(passengers/year/airport).

	Static TWFE	POLS + LDV	Dynamic TWFE	Arellano-Bond	QML
	Coeff. (Std.E.)	Coeff. (Std.E.)	Coeff. (Std.E.)	Coeff. (Std.E.)	Coeff. (Std.E.)
L.log_pax	–	1.002**	0.776**	0.624**	0.974**
	–	(0.003)	(0.016)	(0.081)	(0.036)
Treated 2011	−0.100*	−0.068**	−0.113**	−0.100**	−0.109**
	(0.037)	(0.024)	(0.014)	(0.028)	(0.031)
Treated 2012	−0.114**	−0.029	−0.063**	−0.071	−0.041
	(0.022)	(0.033)	(0.020)	(0.044)	(0.039)
Treated 2013	−0.050	−0.018	−0.033	−0.014	−0.019
	(0.058)	(0.022)	(0.030)	(0.047)	(0.027)
Treated 2014	−0.051	0.017	−0.029	0.009	−0.001
	(0.076)	(0.016)	(0.021)	(0.051)	(0.030)
Treated 2015	−0.010	0.034	−0.009	0.036	0.015
	(0.095)	(0.022)	(0.033)	(0.052)	(0.037)
Treated 2016	−0.085	−0.033	−0.073*	−0.032	−0.047
	(0.080)	(0.022)	(0.026)	(0.055)	(0.030)
Treated 2017	−0.132	−0.008	−0.066*	−0.042	−0.033
	(0.075)	(0.020)	(0.024)	(0.050)	(0.030)
Treated 2018	−0.157*	−0.004	−0.068*	−0.047	−0.030
	(0.076)	(0.018)	(0.025)	(0.054)	(0.029)
Treated 2019	−0.173*	−0.014	−0.077**	−0.054	−0.037
	(0.071)	(0.039)	(0.016)	(0.072)	(0.048)
GDP/cap	0.723**	−0.031**	0.161*	0.335**	0.047
	(0.216)	(0.007)	(0.063)	(0.082)	(0.048)
Accomod. Price	−0.008*	0.000	−0.002	−0.005**	−0.001
	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)
Terror attack	−0.005	−0.011	0.017	−0.003	0.011
	(0.036)	(0.008)	(0.010)	(0.011)	(0.010)
Pre-treatment dummies	Not significant	Not significant	2006, 2007 significant	Not significant	2006 significant
Fixed effects:					
Airport	Yes	–	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N observations	4110	3822	3822	3536	3795

Note: ** and * indicate statistical significance at the 1% and 5% level respectively. Standard errors are reported in parentheses and clustered at the country level. All models include pre-treatment dummies for 2006–2009. Differences in number of observations are due to inclusion of lagged variables and use of lagged variables as instruments.

Table 3
Results for sample excluding hub airports. Dependent variable is log(passengers/year/airport).

	Static TWFE	POLS + LDV	Dynamic TWFE	Arellano-Bond	QML
	Coeff. (Std.E.)	Coeff. (Std.E.)	Coeff. (Std.E.)	Coeff. (Std.E.)	Coeff. (Std.E.)
L.log_pax	–	1.001**	0.771**	0.624**	0.969**
	–	(0.004)	(0.016)	(0.075)	(0.039)
Treated 2011	−0.123**	−0.089**	−0.134**	−0.119**	−0.129**
	(0.043)	(0.026)	(0.015)	(0.031)	(0.034)
Treated 2012	−0.144**	−0.043	−0.080**	−0.089	−0.054
	(0.024)	(0.038)	(0.021)	(0.050)	(0.045)
Treated 2013	−0.068	−0.025	−0.039	−0.023	−0.022
	(0.060)	(0.025)	(0.031)	(0.052)	(0.030)
Treated 2014	−0.071	0.020	−0.027	0.007	0.005
	(0.079)	(0.019)	(0.021)	(0.057)	(0.033)
Treated 2015	−0.023	0.043	−0.001	0.040	0.028
	(0.099)	(0.026)	(0.034)	(0.059)	(0.042)
Treated 2016	−0.100	−0.032	−0.071*	−0.033	−0.041
	(0.082)	(0.026)	(0.027)	(0.062)	(0.035)
Treated 2017	−0.144	0.001	−0.059*	−0.037	−0.021
	(0.076)	(0.023)	(0.025)	(0.057)	(0.034)
Treated 2018	−0.174*	−0.005	−0.070*	−0.051	−0.028
	(0.077)	(0.021)	(0.025)	(0.060)	(0.033)
Treated 2019	−0.207**	−0.031	−0.096**	−0.074	−0.051
	(0.070)	(0.045)	(0.015)	(0.081)	(0.056)
GDP/cap	0.741**	−0.033**	0.175*	0.344**	0.053
	(0.237)	(0.007)	(0.070)	(0.089)	(0.053)
Accomod. Price	−0.009**	0.000	−0.003*	−0.005**	−0.002
	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)
Terror attack	−0.001	−0.009	0.018	−0.002	0.012
	(0.038)	(0.008)	(0.011)	(0.011)	(0.011)
Pre-treatment dummies	Not significant	Not significant	2006, 2007 significant	Not significant	Not significant
Fixed effects:					
Airport	Yes	–	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N observations	3765	3500	3500	3237	3473

Note: ** and * indicate statistical significance at the 1% and 5% level respectively. Standard errors are reported in parentheses and clustered at the country level. All models include pre-treatment dummies for 2006–2009. Differences in number of observations are due to inclusion of lagged variables and use of lagged variables as instruments.

the effects of the tax, the static TWFE estimate's coefficients are, once again, largest (in absolute value), except for 2011. All regressions find a statistically significant decrease in passenger numbers for 2011 with the effect size ranging from −9% to −13%. In general, the effect sizes are larger for the sample that excludes hub airports. The static and dynamic TWFE estimations also find statistically significant effects for 2012, of −13% and −8%, respectively. Results for after 2013 follow the same pattern as with the previous results, where only static and dynamic TWFE find statistically significant effects after 2016. As noted in Section 4, the static TWFE may lead to an overestimation of the effect size. This may explain the large and significant effect sizes produced by this model in later years. In the next section we will assess the existence of these patterns in a wider range of specifications using the Specification Curve Analysis.

6. Specification curve analysis

For this study, three categories of specification characteristics are analyzed via Specification Curve Analysis (SCA) regarding their effect on estimation results (see Table 4): variations over the type of econometric model or estimator (labelled K1 in the figures),

Table 4
Estimators, covariate characteristics, and data subset characteristics which were combined for SCA.

Estimators used (K1)	Covariates and dummies used (K2)	Data subset used (K3)
A. Fixed Effects (FE)	1. As in main regressions	i. As in main regression
B. Pooled OLS + LDV	2. Include transport prices index (HICP)	ii. Only airports with complete data (2005–2019)
C. FE + LDV	3. Include kerosene price	iii. Drop highest/lowest 0.5 % of datapoints
D. Arellano-Bond (AB)	4. Prices in logs	iv. Keep "irregular" airports
E. Quasi-Maximum Likelihood (QML)	5. No pre-treatment dummies	v. Only years 2007–2019
		vi. Include neighboring airports (with dummy)
		vii. Include other taxed countries
= 5 variations	= 5 variations	= 7 variations
= 175 combinations (5 x 5 x 7)		

variations over covariates and dummy sets (K2), and variations on the specific data subset which was used for estimation (K3).

Set K1 comprises the estimators discussed in Section 4.1, namely a two-way fixed effects (static TWFE) estimator applied to the static model, a Pooled OLS estimator applied to a dynamic model (POLS + LDV), a fixed effects estimator applied to a dynamic model (dynamic TWFE), an Arellano-Bond estimator, and a Quasi-Maximum Likelihood (QML) estimator.

The specification variants in set K2 begin with the covariate configuration as they were in our main specifications (labelled “No changes”) and then iterate over the following changes (one-by-one): no pre-treatment dummies; log-transforming the accommodation prices; including kerosene fuel prices as a proxy for ticket prices; and including generalized transport prices (Harmonized Index of Consumer Prices, HICP, for transport) as a proxy for ticket prices.

The specification variants in set K3 begin with the configuration from our main specifications (labelled “No changes”) and then iterate over the following changes (one-by-one): not excluding countries with major change in aviation tax from control group; including neighboring airports as an additional treated group; use data for 2007–2019; including airports with irregular data; dropping the largest and smallest 0.5% of observations; including only airports with complete datasets.

Each estimator (K1) is then used to estimate models using five different sets of covariates (K2) times seven different data subsets (K3). These variations and their combinations make up our robustness testing in the way of the Specification Curve Analysis. The combination of the five different estimators (K1 = 5), with five variations in covariates (K2 = 5), and seven changes in the data subset (K3 = 7), yields a total of 175 model specifications (see Table 4).

Fig. 3 shows the Specification Curve Analysis (SCA) plot for the coefficient of the 2011 treatment dummy for estimations run with data for all airports. The top panel shows the estimated coefficients, sorted by magnitude, and indicates whether they are statistically significant at the 5% level with a black dot; a grey cross indicates a coefficient that is not statistically significant. Red diamonds indicate the results reported in Table 2. The particular specification producing each estimate is indicated in the bottom panel, where a clustering of dots indicates that a certain characteristic may have a strong consistent effect on estimates. We present the figures for all other post-tax years (2012–2019) in Appendix D.1.

For 2011, virtually all estimates are statistically significant with effect sizes ranging from -6% to -14%. There are few clear correlations between specification and outcome. In line with the bracketing relationship mentioned above, effect sizes from the static TWFE model are consistently larger (i.e. a more negative coefficient) than effect sizes from the dynamic POLS model. Effect sizes from the Arellano-Bond model are generally also larger than those from the dynamic POLS model. The SCA plot suggests that other specifications do not consistently lead to larger or smaller effect sizes.

While varying the estimator has the abovementioned clear effects on effect estimates, the variations in covariates which were tested (K2) do not. Any tested variation, be it the inclusion of a flight price proxy via kerosene price or not including the pre-treatment dummies, has a relatively even spread of estimate sizes and can therefore be interpreted as having no systematic effect on our results. Variations on the subset of data (K3) mostly also show an even spread of effect estimates. There is some clustering on the more extreme ends for specifications where neighboring airports were included, and when the previously excluded countries were included. The former clustering seems to stem in large parts from estimations with dynamic OLS only. The remaining variations on data subset do not lead to any clustering of effect sizes and it can therefore be concluded that the estimated effects are robust to those variations.

The plot for the 2012 tax effect coefficients (sample with all airports; see Appendix D.1) shows that less than half of the estimated

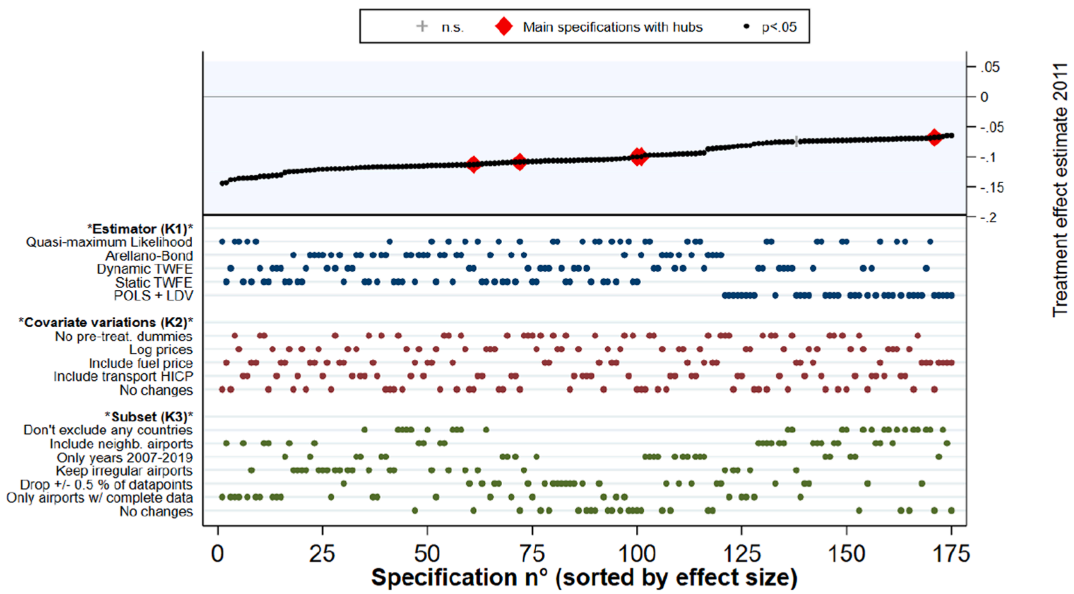

Fig. 3. Specification curve plot for estimates of tax effect in 2011, displaying results of 175 regression with number of passengers/airport as dep. variable and using data for all airports.

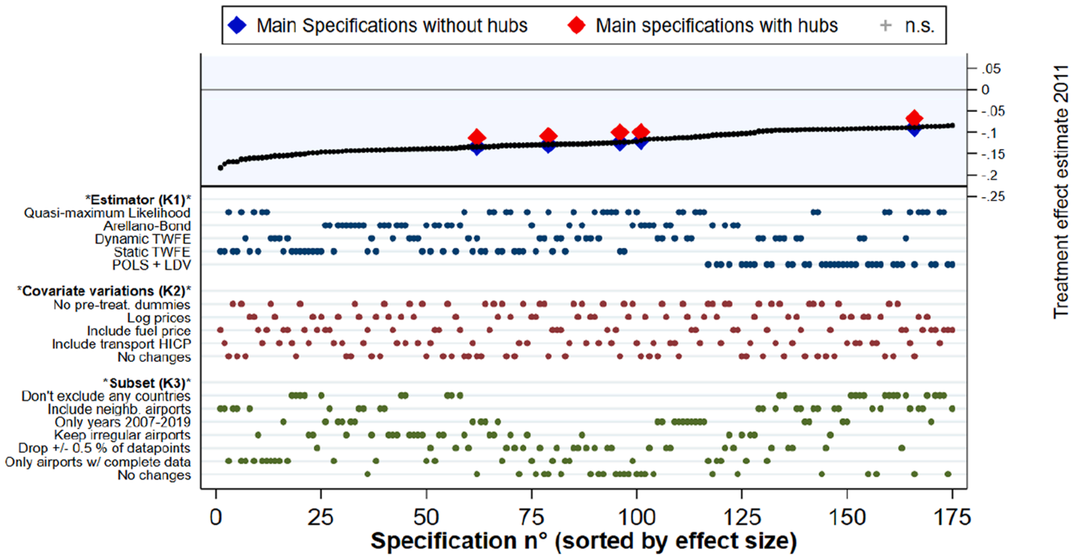

Fig. 4. Specification curve plot for estimates of tax effect in 2011, displaying results of 175 regression with number of passengers/airport as dep. variable and excluding data for hub airports.

coefficients are statistically different from zero. Most significant coefficients stem from the dynamic TWFE model and the Arellano-Bond model, with effect sizes ranging from -5% to -18%. For 2013–2015 the number of statistically significant coefficients is virtually zero. For the years 2016–2019 the share of statistically significant coefficients increases again. Almost all of these latter years' significant coefficients stem from the static and dynamic TWFE estimators.

Fig. 4 shows the specification curve plot of the 2011 treatment effect estimates when excluding hub airports from the data. The blue diamonds indicate the 2011 coefficients reported in Table 3, and the red diamonds indicate those from Table 2, with hub airports included for comparison. Again, there appear to be few correlations between specifications and effect sizes, except for the notable absence of overlap in effect size ranges between the TWFE model and the dynamic POLS model. All coefficients are statistically significant, with effect sizes ranging from −8% to −17 %. Estimates from this sample result from a narrower group of airports (the smaller and generally more low-cost airports), but the data also includes fewer untaxed passengers due to a much smaller percentage of transfer passengers at these kinds of airports. Specification Curve plots were also compiled for the subsequent years. For 2012 (Appendix D.2) we find that less than half of the estimated coefficients is statistically significant, with effect sizes slightly larger than for the sample including hub airports. For later years, fewer significant coefficients are found than for the sample including hubs, with again almost all significant estimates coming from the static and dynamic TWFE model.

An overview of the ranges of the (statistically significant) effect estimates found through our SCA for all years can be found in Table 5. In short, the SCA corroborate our results presented in the previous section. They suggest that the tax had a clear effect on passenger numbers in 2011, with a reduction of 4–13% on all airports and 8–17% when looking only at non-hub airports. Over 99% of the 175 specifications found a statistically significant negative effect for 2011. For 2012, the fraction of statistically significant estimates goes down drastically to 38% for the sample with all airports and 33% for the sample with only non-hub airports, and similar ranges of effect sizes (4–14% reduction and 5–18% reduction, respectively). For 2013, none of the 175 specifications found any significant effects, for 2014 almost none, and for the years following that, this percentage rises again, with a surprisingly large percentage of significant effect estimates for 2019 (33% and 39%, respectively). Interestingly, these significant coefficients are produced overwhelmingly by the static and dynamic TWFE models, but not by any other estimators.

Table 5
Summary of estimated annual effect sizes, based on 175 specifications within SCA.

All airports	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Proportion of significant coeff. ($p < 0.05$, 175 specs.)	99%	38%	0	2%	5%	10%	13%	20%	33%
Lower bound estimate	−13.50%	−13.6%	0	−5.3%	4.5%	−8.2%	−15.5%	−17.8%	−19.7%
Upper bound estimate	−6.3%	−3.7%	0	2.7%	9.1%	−4.4%	−5.6%	−3.4%	−4.1%
Non-hub airports	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Proportion of significant coeff. ($p < 0.05$, 175 specs.)	100%	33%	2%	0.6%	5%	6%	12%	23%	39%
Lower bound effect size	−16.7%	−17.4%	−14.4%	−14.4%	4.9%	−16.6%	−18.2%	−20.9%	−24.0%
Upper bound effect size	−8.1%	−4.6%	−14.4%	−14.4%	10.2%	−4.5%	−5.1%	−3.7%	−4.6%

7. Discussion

The results of our main specifications suggest that the German aviation tax led to a reduction of 7–11% in the number of passengers departing from German airports in 2011. A more precise estimate of the effect of the tax on passengers that are actually subject to the tax can be obtained by excluding hub airports, as these have large numbers of untaxed transfer passengers. In doing so, our main models find an effect of 9–13% reduction in 2011. In our sensitivity analysis via Specification Curve Analysis (SCA) we find slightly wider ranges, of 6–14% and 8–17%, respectively.

For 2012, the second year after implementation, only two of our main models find significant effects, with −6% and −11% in the models with all airports, and −8% and −13% in the models excluding the hub-airports. Within the SCA for the effect in 2012, ranges of effects sizes are −4% to −14% for the full sample and −5% to −17% when looking at non-hub airports only. The fraction of regressions that resulted in statistically significant estimates for 2012 decreased markedly from that in 2011.

For 2013 and 2014, extremely few significant effects were found, both in our main models and in the SCA. This indicates that the tax seemed to have a short-lived but strong effect in the first two years after its introduction.

For 2015 and later, the results are more ambiguous. In our main models, only the static and dynamic TWFE models found effects after 2012. This pattern is repeated in the SCA, where there are a notable number of statistically significant coefficient estimates for 2016–2019. These are produced almost exclusively by the models using static or dynamic TWFE estimators, with the effect sizes from the static TWFE models being almost always larger than those of any other model. As noted in Section 4, the static TWFE may lead to an overestimation of the effect size. Indeed, for the final years in our sample the effect sizes from this model exhibit magnitudes that seem largely implausible (up to −24 % effect), especially when consulting the initial plots of development over time (Figs. 1 and 2). That the tax has a larger effect in 2016–2019 than in 2011 is improbable; therefore, these estimates should be treated with caution. Still, on the basis of our SCA, we cannot entirely rule out that the tax had an effect after 2014.

We can compare our findings for 2011 to the literature on air fare price elasticities. Eurostat provides a harmonized country-level price index for passenger transport by air (Eurostat 2021b). We did not include this variable in our models as it constitutes a bad control: air fares are themselves affected by passenger taxes due to cost pass through. From 2010 to 2011 in Germany, the index records a price increase of 13.4%, a much higher increase than in most other years. The mean price increase from 2010 to 2011 in the control countries (as used in our main models) is 2.1%. Hence, the relative increase in German air fares relative to that in the control group is 11.1%. This relative increase may, at least partly, be attributed to the introduction of the aviation tax in Germany. From literature (Granados et al. 2012, Morlotti et al. 2017, Mumbower et al. 2014), we get a range of air fare demand elasticities of −0.34 to −2.28. Based on these elasticities, the additional price increase in Germany of 11.1% between 2010–2011 would lead to a change in passenger numbers of −3.8% to −25.2%. The effect sizes for 2011 that we derive from our SCA (see Table 5) fall in this range.

When comparing our results to those found in the literature, we find the following: Borbely (2019), who uses the synthetic control method for his analysis, estimates that the German aviation tax reduced the annual number of passengers at German airports by 2% in the years 2011–2015. Our SCA results for the full sample show a range of effect sizes between 3.7% and 13.6% reduction in the same years. While these estimates are larger than Borbely's, one must take into account that his 2% are an overall effect estimates for the whole period. When considering that our SCA estimations returned very few significant effect estimates in 2013–2015, a rough averaging of effects between significant and non-significant years gives a similar vicinity of 2–6%.[3] The remaining differences may be caused by the differences in the methods used. Falk and Hagsten (2019) use a dynamic panel data model with the quasi maximum-likelihood estimator, which is also one of the estimators we use. Their effect sizes for 2011 and 2012 fall within the ranges of our SCA for partial effects, albeit towards our lower bounds. For 2013–2015, however, our SCA finds only a handful of statistically significant results on a total of 175 regressions. Falk and Hagsten (2019) find a significant effect for 2014 for their full sample and significant effects for 2013 and 2015 for their restricted sample. They also find significant effects for 2016 (the last year in their sample) for both their samples, while in our SCA only about 10% of the estimates for that year are statistically significant. Bernardo et al. (2024) analyze the average joint impact of the German, Austrian, Norwegian and Swedish taxes on the number of flights. Their effect sizes are within our range of estimates for effects on the number of passengers.

The results for our main specifications show that different econometric models and estimators can lead to different results, both in terms of statistical significance and effect sizes, especially for later years. Moreover, choices made by the researcher about covariate selection and data configuration have a major effect on the reported results. Indeed, according to our SCA, the results found by Falk and Hagsten (2019) for 2013 and later seem to be the result of a specific configuration of the regression equation and the dataset used rather than a general result from a wide range of specifications.

Throughout the paper we have made a distinction between the sample based on passenger numbers from all airports and the subsample that excludes hub airports. Since non-hub airports have few transfer passengers, almost all passengers in the latter subsample are subject to the tax. We consistently find larger effect sizes for this subsample. There can be various reasons for this. First of all, it is possible that the estimated effect sizes for the subsample that excludes hub airports are more precise estimates of the "average treatment effect on the treated" as transfer passengers, who are not subject to the tax, are excluded from the sample. Secondly, it could be that the estimated effect sizes are larger because the passengers departing from non-hub airports are different from those departing from hub airports. For example, larger airports are likely to have more business travelers who tend to be less sensitive to price changes, while passengers at non-hub airports may, on average, be more responsive to such price changes (Brons et al. 2002, Hess and Polak

[3] Numbers based on the minimum and maximum effect estimates in our SCA, for the sample including hubs, the years 2011–2015, and using summed up passenger numbers. For 2013 and 2014 an effect of 0% is assumed. Minimum value based on a value of zero for 2015.

2005, Morlotti et al. 2017, Bernardo et al. 2024).

Another potential factor is rooted in the differences between large, internationally-flying airlines – also called network airlines – and smaller, low-cost ones. Large airlines have more classes to offer, with prices varying widely between the lowest and most expensive classes. To compensate for the tax burden, these airlines can raise the prices of the higher classes more than for the lower classes and are therefore not as pressured to compensate for it in other ways on the supply side. Larger airlines also have a more diverse fleet and can adjust more flexibly to demand by switching out larger airplanes with smaller ones and vice versa. Smaller airlines have fewer opportunities in both regards and are more likely to adjust to the cost by scrapping a number of flights altogether. Alternatively, they can increase the price of their overall more affordable tickets, which is more likely to be noticed by their customers (Zuidberg 2015, Thelle and la Cour Sonne 2018). Since non-hub airports are mainly serviced by smaller airlines, it is then apparent that passenger numbers at those airports were affected more strongly than those at hub airports.

The tax was announced a few months in advance and was not raised significantly in the years of observation, which gave airlines the chance to adjust their pricing strategies over time in order to account for this additional financial burden. A large part of the effect, as detected by our analysis, may have been driven by changes on the supply side, where airlines adjusted the number of seats and routes offered over the short-term in reaction to the tax, and then adjusted aspects like add-on pricing over the longer term, returning to pre-tax levels of seats offered. Altogether, this would lead to an overall decreasing effect of the tax, which is precisely what we observed in our estimations. Add-ons such as priority boarding, a larger carry-on, or fast-track security passes became ubiquitous in the years since the tax was implemented. The income made from these add-ons may have helped balance out the tax burden for airlines in the long run. This could especially be the case for smaller and low-cost ones, who often have a smaller profit margin but also lower prices, and thus are not able to pass on 100% of the tax costs.

The COVID-19 pandemic has led to a strong fall in demand for flights, at least during and in the immediate aftermath of the pandemic. During the pandemic, passengers' willingness to travel decreased due to anxiety and perceived health risks, and partly because of the increase in remote meetings (Combs et al. 2024, Morlotti and Redondi 2023). In response, airlines reduced prices, and network airlines did so more than low-cost airlines (Borsati and Fageda 2024). We do not know whether cost pass-through of the German aviation tax is still (13 years after its introduction) explicitly part of the pricing strategies of airlines. Still, lower prices could mean that a smaller part of an aviation tax (whether new or existing) is passed through to customers, at least until the aviation market has bounced back to pre-COVID levels.

As mentioned above, passenger data from hubs comes with some caveats. Extant datasets make no distinction between transfer passengers that did not begin their journey at the recorded airport of departure and other departing passengers that did. Since the German aviation tax does not apply to transfer passengers, such data will not be able to accurately reflect the response to the tax of all passengers flying out of Germany. It mixes treated and untreated groups of passengers, and therefore any result for the effect of the tax on taxed passengers based on data from hub airports will be biased. This is not an unimportant shortcoming, since hub airports make up a notable proportion of aviation traffic in any country. Until reliable and long-run data on transfer passengers at hubs is available, studies intending to depict per-passenger tax effects in detail, especially at the airport level, will continue to fall short. However, for policymakers or researchers interested only in the larger-scale country-level effect of a passenger tax, the current detail in the data may be sufficient.

8. Conclusions

To determine the effect the German aviation tax had on passenger numbers after its implementation in January 2011, we used Eurostat panel data on annual departing passenger numbers per airport in static and dynamic two-way fixed effects and dynamic ordinary least squares models. To allow for the possibility that the effect of the tax dissipates over time, we used an event-study approach that captures annual effects individually.

For the years 2011 and 2012, a large proportion of our models returned statistically significant effect estimates, both when estimating with data from all airports and when estimating with data from non-hub airports. For the former, the estimated effects of the tax on passenger numbers at German airports ranges from −6% to −11%. For the latter (i.e. the estimations using only non-hub airports), the estimated effect of the tax on passenger numbers at German airports is slightly larger and ranges from −9% to −13% in those two years. In a Specification Curve Analysis, which included regressions using 175 alternative specifications on the same subject, the ranges were slightly larger, specifically between −4% and −14% for estimations with all airports and between −5% and −17% for estimations excluding hubs. We reported effect ranges here, because our analysis also shows that the choice of estimator has a non-negligible effect on the magnitude of the effect estimate. Since all estimators used in this study have merit for this particular dataset and analysis, we choose to report the range of estimated effects instead of just a specific, single number. Looking at the results from our SCA, the tax appears not to have had an effect on passenger numbers in 2013 and 2014. However, an effect of the tax on passenger numbers after 2014 cannot be ruled out as the fraction of our models reporting a statistically significant effect is non-negligible. Still, these estimates tend to become unrealistically large, returning magnitudes of up to −24%, which does not seem likely when looking at the general development of passenger numbers over time. Indeed, all unrealistically large effect estimates in later years are the result of estimations using static TWFE, which may be prone to overestimating effect sizes when the underlying data is more suited for a dynamic modelling approach.

Throughout our analysis we distinguished the results based on a dataset including all airports from the results based on a subset excluding all hub airports. The motivation for this is that hub airports serve large numbers of transfer passengers, who are not subject to the tax. For a precise estimate of the effect of the tax on taxed passengers (the average treatment effect on the treated), annual data on the number of transfer passengers at the airport level would be needed. We find that excluding hubs leads to larger effect estimates, which may be due to the prevalence of transfer passengers as well as to the specific characteristics of hub versus non-hub airports.

The aim of the tax was threefold: to generate additional tax income, to end the exemption of air travel from mobility taxes, and to create incentives for environmentally-friendly behavior. According to publicly available data, the tax continues to fulfill its original purpose of raising additional annual income for the federal government of Germany. Its success in fulfilling its environmentally motivated goals, however, is less clear. Tax-induced environmentally-friendly behavior of German citizens would mean an increase in using alternative travel modes. The tax did lead to a decrease in the number of departing passengers at German airports, at least in the first two years after implementation. To what extent this has reduced emissions depends on the number of flights, the destinations, and the size of leakage. After all, partially filled planes still fly and emit greenhouse gases. Our results suggest that, assuming that occupancy rates have not decreased after the tax, the tax induced at least an emission reduction in the first two years, and that we cannot rule out that there was a structural decrease in emissions. However, we cannot confidently conclude that the tax has continued to negatively affect passenger numbers at German airports over the long term. Still, pricing aviation's effect on the climate into the market is a vital part of sustainably transforming transportation and making a tax more flexible to reflect the price of CO_2, or a better integration of aviation into emissions trading systems, may prove promising in this regard.

CRediT authorship contribution statement

Viola Helmers: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Edwin van der Werf:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2024.104570.

Data availability

Data will be made available on request.

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